# Digital payments, transaction costs, and household resilience in Sub-Saharan Africa

by

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B.S., National Polytechnic Institute of Côte d'Ivoire, 2001
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

The weak participation in output markets and poor access to risk management tools for farm and non-farm enterprises stand as major impediments to the sustainable provision and access to food in developing countries. Rural households incur substantial transaction costs to reach output markets. In addition to their effect on market access, high transaction costs could also hinder the delivery of financial services that could presumably enable efficient risk management. Thanks to their low cost, security and rapid delivery features, digital payments present tremendous potential to improve the rural enterprise environment. However, little evidence is known about the potential role of digital payments in output market efficiency and risk management. Essay 1 focuses on digital payments and market participation while Essay 2 explores how digital payments can contribute to building resilience to income shocks.

In Essay 1, we develop and test a conceptual model in which digital payments improve market participation by lowering transaction costs. Here we show that the use of mobile money is associated with a reduction of information asymmetry around the buyer type and a large gain in welfare for distant market participants. The predictions of the conceptual model are empirically tested using an instrumental variable approach and secondary data from a cross-sectional survey conducted by the Consultative Group to Assist the Poor (CGAP) in Cote d'Ivoire and Tanzania. A special regressor model estimates the probability of distant market participation increases on average by 55 percentage points for mobile money users. Furthermore, we rank marketing venues based on hold-up risk and find that the effect of mobile money is most prominent for decisions to switch from village to local market sales outlets. Our results demonstrate how farm and non-farm enterprise owners would benefit from the spread and access to digital payments beyond the traditional pathway of credit, savings, and remittances.

Essay 2 attempts to understand how digital payments enhance risk management capabilities and contribute to building household resilience to future shocks. Our outcome of interest is the Barret and Constas (BC) development resilience measure that embodies the capacity of a household to avoid falling below a threshold poverty level in the face of shocks and stressors. We first construct a multidimensional index of well-being based on productive asset holdings and empirically investigate the effect of mobile money on household development resilience using a conditional moment approach.  The dataset exploited consists of secondary data from a 4 rounds panel of households representative of the national population of Kenya. We found that a 10 km reduction in the distance separating households from the nearest mobile money retailer results in a percentage point increase in development resilience. Moreover, wealthier households are more likely to benefit from higher access to mobile money. When facing severe shocks, mobile money users were found capable of sustaining a higher probability of exceeding the asset poverty line than their non-user counterparts. The findings of Essay 2 establish new evidence on the long-run effect of digital payments.

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# Dedication

To my father, N'Goran Yao, who has always believed in my abilities, my mother, Amoin Tchimi, my beloved wife, Amandine, and my lovely kids, Ashley, Evan, and Nohemie.

# Chapter 1 - Introduction

Food security has become a major topic of concern in the last decades. The risk of food insecurity brought by the growing population projected to hit 9 billion by 2050 stresses the urgent need for improved access to and more efficient use of capital and markets. This rapid demographic growth mainly takes place in developing countries where over 40% of the active population work in the agricultural sector (World Bank, 2017). Addressing the challenges of agriculture mitigates the threat of food insecurity while improving the livelihood of vulnerable communities. Although beneficial to vulnerable communities in the short-run, numerous programs and initiatives revolving around the transfer of assets, cash or inputs have faced the persistent issue of sustainability. Some types of interventions that promote self-employment seem to establish lasting but small improvement in welfare (Banerjee et al., 2015).

Knowledge and information have always played a major role in agriculture (World Bank, 2017) and income-generating activities in rural areas. Whether at the production, management or marketing level, households that have better access to information and knowledge are likely to make the best decision that makes a lasting impact on their livelihood. Agriculture is becoming increasingly knowledge-intensive, especially with the multiple challenges caused by weather-related shocks, high food price volatility and inefficient supply chains (FAO and ITU, 2016). As with the industrial revolution that fostered enormous gain in cost and efficiency and gave a big push to all aspects of humanity, the digital revolution has the potential to impact agriculture and food security by reducing the cost of information and exchange. The large scale adoption of such technologies in the last decade has paved the way for the development of mobile-based services that could be leveraged to provide market-driven solutions to smallholders' agricultural challenges. Unlike transfer based programs and interventions that can potentially generate negative externalities or general equilibrium effects, digital-based solutions are driven by the spontaneous adoption of mobile phones. The benefits of this type of solution are best expressed in the argument of the economist William Easterly summarized as: “When markets are free and the incentives are right, people can find ways to solve their problems” (Banerjee and Duflo, 2012).

Digital payments present three well-known advantages to their users in developing countries. First, they provide a quasi-instantaneous and accessible method to transfer money at low cost with few investments needed compared to other informal methods such as in person or through a bus driver, or more formal methods provided by banking and related institutions. Second, digital payments allow the unbanked to access financial services such as credit and savings that would be otherwise unreachable. Finally, they generate valuable data for credit profiling and other usages which allow offering tailored services to rural populations. Because of their potential impact on household livelihoods, there is a growing interest in digital payments.  Yet, the empirical literature in this area is still nascent and relatively unvaried. This dissertation investigates the impact of digital payments in two key areas that have received scant attention from the literature: (i) Output market access and (ii) risk management.

Our contribution to the digital payments literature is twofold. First, in essay 1 we provide a methodological contribution to the existing body of work. The impact of digital payments to rural development in a broad sense has always been explored from the perspective of their low cost of transfer. In this vein, Suri and Jack (2016), Munyegera and Matsumoto (2016) and Kikulwe et al. (2014) provide solid empirical evidence of the enhanced welfare resulting from the cost-saving feature of mobile money. However, when digital payments are merely perceived as instruments to reduce the cost or to increase the speed of money transfers, their welfare effect could hardly be separated from intrinsic savings or risk-sharing behaviors exhibited by the individual of interest prior to using the technology. Because digital technologies fundamentally cut the cost of information, one would expect these technologies to influence the transaction costs resulting from the lack of information by one of both of the transacting parties. Our study examines the welfare effect of mobile money using the framework of transaction costs economics, which allows us to leapfrog the basic cost-reducing function of mobile money. By testing this novel methodological approach in two leading mobile money adopting countries, we provide empirical evidence of the transaction cost reduction pathway of mobile money.

Essay 2 provides new evidence of the longer-run effect of mobile money. Existing studies focus on the short-term effects of mobile money, one exception being Suri and Jack (2016). Either the lack of datasets spanning over a sufficiently long period or the focus on a short run outcome explains the relatively scarce literature on the long-run effects of mobile money. In this study, we employ a novel measurement of resilience to understand what could be the impact of mobile money on an outcome that predicts a long run state of welfare. Our outcome of interest is the Barret and Constas (BC) development resilience metric that particularly embodies the capacity of a household to avoid falling below a threshold poverty level in the face of shocks and stressors. In addition, by focusing on productive assets, this study provides evidence of a positive relationship between mobile money and risk management of income-generating activities. To the best of our knowledge, this is the first study that utilizes the concept of development resilience to investigate the effects of digital payments.

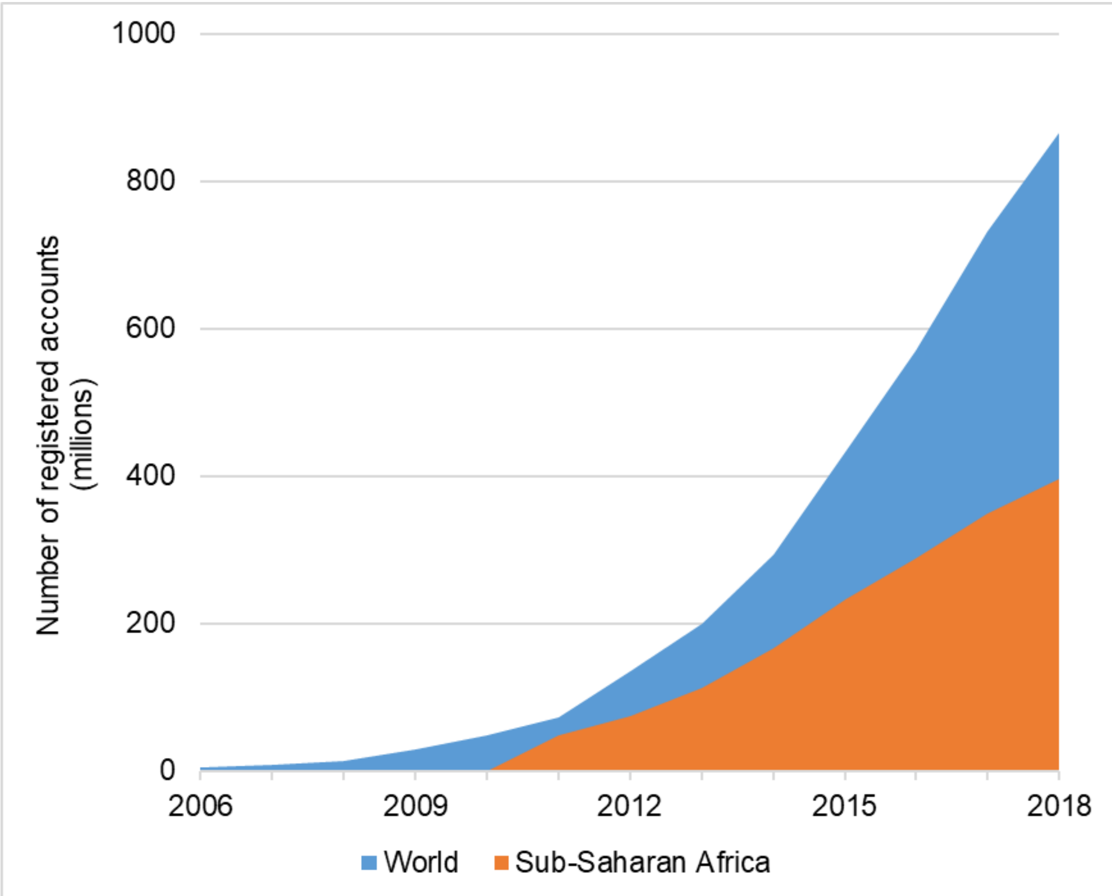


**Figure 1.1 Registered Mobile Money Accounts**

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# Chapter 2 - Mobile money, Signaling, and Market Participation: Evidence from Tanzania and Cote d'Ivoire

## Introduction

Market participation has been shown to improve rural household income (Alene et al., 2008; Olwande et al., 2015), however for many smallholder agricultural producers in developing economies market access remains constrained by high transaction costs. Policy initiatives such as price subsidies and infrastructure investments have yielded mixed results in enhancing market participation (Poole, 2017). Recent empirical evidence from studies in Central America, Eastern Europe, and Sub Saharan Africa has shown that the costs associated with transportation and aggregation only partially explain low levels of market participation (Olwande et al. 2015, Hellin et al., 2009). In the transaction cost economics literature, a significant proportion of market linkage failures has been attributed to costs associated with information asymmetry and potential opportunistic behavior of transacting parties (Blandon et al., 2009). This is particularly true in countries with underdeveloped or inadequate market information systems and public enforcement mechanisms. Consequently, policymakers, agribusiness, and agricultural development scholars are in a continuous search for innovative solutions for reducing information asymmetry and facilitating market linkages based on private enforcement mechanisms (Guo and Jolly, 2008; Narrod et al., 2009; Sartorius and Kirsten, 2007).

### Mobile money and welfare effects

The digital revolution in the last decade has paved the way for wide-scale adoption of digital technologies such as mobile technologies that could be leveraged to provide market-driven solutions to smallholders' agricultural challenges in Sub-Saharan Africa. Mobile money, a money transfer technology that was first popularized in Kenya, not only offers banking products to previously unbanked households but also provides a fast and low-cost money transfer method to facilitate market transactions. The potential solution that digital technologies can provide to smallholder's issues is demonstrated by the growing literature around digital technologies in agriculture and their contribution to smallholders' welfare. Most of the work regarding digital technologies rely on success stories and case studies of digital application that improve farmers' welfare. Protopop and Shanoyan (2016) is a collection of successful applications of digital technologies in the agri-food industry of developing countries. Since the advent of mobile money services in 2007, a handful of econometric studies have investigated their economic impact in Kenya and found a positive effect. Reflecting this, Mbiti and Weil (2011) concluded that mobile money contributes to decreasing the price of traditional money transfer services and improving financial inclusion in Kenya. The welfare effect of mobile money was assessed by Jack and Suri (2014), Kikulwe et al. (2014), Munyegera and Matsumoto (2016), Suri and Jack (2016) in Kenya and Uganda. They found that mobile money increased consumption by 13% (Munyegera and Matsumoto, 2016) and 12% (Suri and Jack, 2016). Along the same lines, Jack and Suri (2014) found that mobile money users were more resilient to economic shocks than their non-user counterparts.

A common finding in the previous literature is that mobile money mainly affects welfare through the pathway of remittance or money transfer from a relative. The lower cost of mobile money transactions relative to traditional money transfer methods results in a higher frequency of money transfers and a more diverse pool of senders (Jack and Suri, 2014). With the increasing number of agents available to process money transactions, households receive money transfers more frequently, which positively affects their consumption and resilience to economic shocks. Two other pathways were mentioned in the mobile money literature: savings and increased market participation. While the savings pathway is discussed in most econometric and case studies, the output market impact pathway was considered only in Kikulwe et al. (2014). They found that mobile money users commercialized 19% more products than their non-user counterparts. Yet, their study discusses the impact of mobile money on market participation based upon the mechanism of remittances that would ease the liquidity constraints on commercialization. In fact, market participation is rather considered as an outcome in their study. This ultimately leads to distinguishing only two pathways through which mobile money may affect welfare. While this is a growing area of interest by policymakers and industry stakeholders, the literature remains underdeveloped with most research to date focusing on the effect of mobile money on welfare through pathways of remittance and improved access to capital. Many questions remain unanswered regarding the role of mobile money in facilitating market participation by reducing the associated transaction costs.

**Mobile money and transaction costs**

The main benefit of using the mobile money technology is its lower cost of transferring money between individuals located far from each other. But the concept of transaction cost in agricultural marketing goes beyond the mere cost of transferring money. Key et al. (2000) and Bellemare and Barrett (2006) discussed two types of transaction costs. The proportional transaction costs include the per-unit cost of accessing markets and are generally associated with transportation and handling while the fixed transaction costs include (a) the cost of searching for a customer with the best price, (b) negotiation and bargaining, (c) screening, monitoring and enforcing an agreement. Another description by Poole (2017) categorized transaction costs as visible and invisible, the latter consisting of search cost and enforcement costs. One strategy to reducing transaction costs consists of lowering the cost of the physical access to markets by improving the institutional and physical infrastructure of the external environment. Another strategy consists of mitigating the costs associated with finding a buyer and/or ex-ante investments to improve the ability of ex-post enforcement in case of violation of the prior agreement by one of the parties (i.e. hold-up). While various interventions have focused on reducing search costs by connecting farmers to buyers (market information systems), ex-post enforcement costs have barely been addressed despite their potential to impede market participation. The existing enforcement instruments are mostly public and generally inefficient due to the inadequate legal infrastructure around agricultural markets in the developing world. However, there is emerging literature pointing out the importance of building trust in market transactions to avoid or mitigate ex-post enforcement costs. Signaling, which involves revealing private information about one of the parties, has particularly been found to improve market participation by reinforcing trust between sellers and buyers (Granja and Wollni, 2019). Our study evaluates how the mobile money technology can serve as a signaling mechanism to alleviate the uncertainty around the buyer type and improve smallholder market participation

Transaction costs can be affected by mobile money in various ways. Digital technologies in general and digital payments, in particular, are characterized by their potential to reduce the cost of information. That is, they facilitate information exchange. Thanks to its fast and secure payment feature, mobile money can potentially enable buyers and sellers to illustrate their commitment to completing a transaction through various signaling and screening mechanisms. The main objective is to determine whether mobile money can constitute an effective mechanism to alleviate the risk for hold-up that smallholders face in their decision to participate in distant markets, reducing the transaction costs of market participation. To investigate this relationship, we exploit a cross-sectional household survey that provides mobile money usage data for smallholders in two countries: Cote d'Ivoire and Tanzania. The model is empirically estimated using a special regressor approach. The study adds to the literature by establishing support for the existence of a third pathway through which mobile money may impact welfare and market participation.

The remaining of the study is structured as follows. We develop a conceptual model that explains the potential impact of mobile money on market participation in the next section. Then we lay out the empirical analysis and the results and discussion. Finally, we discuss the generalizability of the findings along with ideas about further research around this framework in the conclusion.

# Methods and data

## Conceptual model

In this section, we develop a theoretical framework that explains how mobile money can affect a net seller farmer's choice between a village market (v) and a distant market (d) [1] for selling the production surplus. The distant market offers better terms (e.g. price) but has inherent substantial transaction costs that would incur any seller opting for this market. While the village market presents lower transaction costs, it offers less attractive terms than the distant market. The seller's problem is to select the market that maximizes her profit.

Let's start by examining a one-shot game scenario where one seller and one buyer commit to complete a single commodity transaction in a distant market. In this model, the village market transaction is viewed as a default option that determines the seller's reservation utility.

[1] In all subsequent notations, the subscript d is associated with distant markets while the subscript v is associated with village market.

The extension of the model to include repeated-games and multiple buyers will be discussed later in the section.

In a one-shot game, the seller derives a profit $S$ from the distant market sale at a price $P_D$ after she incurs some transportation cost $M$ and transaction cost $TC$. The transaction cost $TC$ arises from a) search cost associated with finding a suitable buyer (e.g. time and resources spent while searching for a buyer), b) hold-up cost associated with losses due to ex-post renegotiation of terms by an opportunistic buyer, and c) ex-ante investments of time and resources to prevent potential hold-up and improve seller's ability for ex-post contract enforcement[2]. In the Transaction Cost Economics (TCE) literature the term hold-up is defined as ex-post renegotiation of contract terms by one of the transacting parties in an attempt to extract quasi-rents from another party (Klein, 1996). Quasi-rents arise from the transaction-specific investments and are defined as the difference in profits between the agreed-upon transaction and the next-best alternative (Klein et al., 1978; Shanoyan et al., 2014). The buyer acquires from the seller some agricultural products of perceived value $V$ in the distant market while paying her the competitive price $P_D$. The seller will choose to participate in the distant market only if the price offered in the distant market is greater than the price she can obtain in the village market $P_v$ added to the transportation cost $M$. This condition can formally be represented as follows: $P_D = P_v + x + M$ where $x$ is a very small non-zero value. With the distant price offered being at least $P_D$, the farmer will spend $M$ to transport the product to the distant market. Let $q$ be the probability of hold-up. Hold-up will occur $(q = 1)$ if the buyer chooses to offer a lower price after the farmer has incurred the transportation cost and delivered the product to the distant

[2] Please see Key et al. (2000) for detailed treatment of Transaction Costs

market. The lowest hold-up price $P_{Dh}$ acceptable by the seller must yield a higher profit than the next best option of transporting the product back and selling it in the village. This condition can be formally represented as $P_{Dh} = P_v + x - M$.

**Incentive structure without mobile money**

To complete a transaction in the distant market, seller and buyer must engage in a sequential game summarized as follows:

| | | | | |
|---|---|---|---|---|
| The Buyer in a distant market offers $P_D$ | The seller accepts offer if $P_D = P_v + x + M$ where $x > 0$ | The seller incurs $M$ to deliver the good to distant market | The Buyer offers $P_D$ if no hold-up (q=0) or $P_{Dh}$ if hold-up occurs (q=1) | If q=1, the Seller accepts hold-up price if $P_{Dh} = P_v + x - M$. If q=0, seller accepts $P_{Dh}$ and the transaction is completed |

In deciding which market to choose, the seller is considering the following payoff options:

$E[S_d] = [(1-q)(P_D - M)] + [q(P_{Dh} - M)] = [(1-q)(P_v + x + M - M)] + [q(P_v + x - M - M)] = [(1-q)(P_v + x)] + [q(P_v + x - 2M)] = P_v + x - 2qM$

(expected profit from distant market) (1)

$S_v = P_v$ (profit from the village market)

(2)

Therefore, at any $M > 0$, the farmer will choose to sell in the distant market only if she can be guaranteed that $q = 0$.

If the buyer chooses to hold up the transaction, she will receive $\pi_{Dh} = V - P_v - x + 2M$. Without hold-up, the buyer will receive $\pi_D = V - P_v - x - M$. It is clear that under this incentive structure the buyer will always choose to hold up ($q = 1$) since $\pi_{Dh} > \pi_D$. Thus the seller will expect $q = 1$ and will always choose to sell in the village market resulting in a sub-optimal equilibrium of $S = P_v$ and $\pi = 0$.

**Incentive structure with mobile money**

The introduction of mobile money allows for a down payment which reduces the likelihood of hold-up. In the TCE literature, these types of mechanisms are referred to as mutual hostages or private enforcement capital (Williamson, 1983). Essentially, the buyer has to provide a sufficient amount of down payment that will ensure to the seller a higher distant market payoff than the village market payoff even if hold-up occurs ($q = 1$). At the distant market, the seller has already incurred the sunk cost $M$ when comparing the prices offered in the two scenarios: selling at the distant market ($P_v + x + M$) or returning the products to the village market ($P_v - M$). It follows that the optimal down payment that would guarantee a distant market pay-off at least equal to the village market pay-off is $2M$. The resulting sequential game with mobile money enabled down payment is summarized as follows:

| | | | | | |
|---|---|---|---|---|---|
| The Buyer in a distant market offers $P_D$ | The seller accepts offer if $P_D$ =$P_v + x + M$ where $x > 0$, and asks buyer to transfer 2M down payment | The Buyer transfers $2M$ through Mobile Money | The seller incurs $M$ in transportation costs | The Buyer offers $P_D$ if no hold-up (q=0) or $P_{Dh}$ if hold-up occurs (q=1) | The Seller returns 2M if no hold-up or keeps $2M$ if hold-up |

If the buyer signals her commitment to complete the transaction through mobile money, the seller obtains the same pay-off regardless of him being offered a hold-up price or competitive price by the buyer. Under the down payment arrangement, the buyer will receive the same payoff regardless of her choice to hold up or not: the buyer has no longer any incentive to hold the seller up. The mobile money transfer of a down payment from buyer to seller will signal a hold-up free transaction to the seller, providing her an incentive to opt for the distant market. The actual completion of the transaction on the distant market moves buyer and seller out of the sub-optimal equilibrium in (2) and yields a higher equilibrium with new respective payoffs of $S_d = P_v + x$ and $\pi = V - P_v - x - M$. It is worthwhile to mention that the seller's payoff is unchanged, whether she receives a hold-up price or not. In the case the seller receives a competitive price after the down payment transfer, her final payoff consists of $P_v + x + 2M - \mathbf{2M} = P_v + x$, since the seller has no reason to retain the down payment amount $(2M)$ transferred up-front to guarantee a hold-up free transaction. When facing a hold-up price after the down payment transfer, the seller buffers herself against the cost of hold-up by retaining $2M$.

**Table 2.1** presents the agents' payoff matrix under the possible alternatives of no hold-up and hold-up.

**Table 2.1 Payoff matrix**

| | **No hold up** $(\boldsymbol{q = 0, TC = 0})$ | **Hold up** $(\boldsymbol{q = 1, TC > 0})$ |
|---|---|---|
| | Without Mobile money | |
| Seller | $S_D = P_D - M = P_v + x$ | $S_D = P_{Dh} - M = P_v + x - 2M$ |
| Buyer | $\pi_D = V - P_v - x - M$ | $\pi_{Dh} = V - P_v - x + 2M$ |
| | With Mobile Money | |
| Seller | $S_D = P_D + 2M - 2M = P_v + x$ | $S_{Dh} = P_{Dh} + 2M = P_v + x$ |
| Buyer | $\pi_D = V - P_D - 2M + 2M$ $= V - P_v - x - M$ | $\pi_{Dh} = V - P_{Dh} - 2M$ $= V - P_v - x - M$ |

The conceptual model predicts that the use of mobile money will alleviate the risk for hold-up and improve distant market participation.

### Repeated games

The two incentive structures addressed above deal with a one-shot game. The underlying hold-up problem is presented from the perspective of a seller's risk of facing an opportunistic behavior from the buyer, assuming a risk-averse seller and a risk-neutral buyer. In reality, buyers who engage in a transaction with sellers are exposed to hold-up costs that could arise from the delivery of lower quality products or a missing delivery after the down payment is transferred to the seller. In this case, the buyer may not engage in the transaction, fearing to lose her down payment. The repeated game setting provides the conditions for the use of private enforcement capital defined by Gow and Swinnen (2001) as the losses that one of the parties would incur as a result of contract termination and reputational damage. In a repeated game, buyer and seller engage in a long term contractual arrangement where the cost of breaching the contract (hold-up) increases the self-reinforcing range of contractual arrangement, enhancing the overall reliability of the transaction (Shanoyan et al. 2016). The private enforcement capital allows us to relax buyer's risk neutrality assumption in a repeated game.

The buyer-seller contract in a repeated game can be depicted as a principal-agent situation where the principal (buyer) rewards the seller for honoring the contract. The short-run Nash equilibrium derived from the one-shot game is typically inefficient since there is another pair of moves from the two parties that yields a higher expected utility for both the seller and the buyer (Radner, 1985). This would correspond to the seller delivering a lower quality of products or retaining the down payment without honoring the contract. But when buyer-seller transactions are repeated, the incentives are better distributed over time (Macho-Stadler and Pérez-Castrillo, 1997). This is made possible by the buyer's opportunity to penalize the seller for departure from their previous transaction agreement. Radner (1985) demonstrates that the repeated game increases the efficiency of the Nash equilibrium - that is, the repeated game precludes any sub-optimal behavior that would threat the future payoff of both parties, even if they discount their future expected utility.

To illustrate this result, let's consider the buyer's discounted expected utility in period t:

$$U = (1-\delta)\sum_{t=1}^{\infty}\delta^{t-1}U_t \qquad (1)$$

where seller and buyer have the same discount factor $\delta$ and the seller has a similar expected utility function Q. For every pair of one period efficient expected utility $(\widehat{U}, \widehat{Q})$ superior to the one-period expected utility from the actual moves $(U^*, Q^*)$, such that $\widehat{U} > U^*$ and $\widehat{Q} > Q^*$, there exists a discount factor $\delta$ that yields a repeated game equilibrium sufficiently close to the one period efficient expected utility $(\widehat{U}, \widehat{Q})$ (Radner, 1985). A direct implication is that the resulting incentives are comparable to those of the static model above, that it, the incentive structure with mobile money leads to an optimal equilibrium under the assumption of a low discount factor $\delta$. However, this conclusion cannot be drawn from the model in (1) when the seller foregoes her future profit ($\delta$ high). But a high discount rate constitutes a special case, like many others for which the model should be adjusted. From the conceptual model above, the following hypothesis can be formulated - H1: Mobile money improves market participation. Testing this hypothesis will consist of comparing the rate of distant market sales across mobile money users and non-users. If the hypothesis holds, we should observe a higher rate of distant market sales among mobile money users.

## Data

The analysis is based on the Consultative Group to Assist the Poor's Smallholder Household Survey (CGAP-SHS), a nationally representative survey implemented in 5 African countries: Cote d'Ivoire, Mozambique, Nigeria, Tanzania, and Uganda. The main advantage of the CGAP-SHS is to incorporate a detailed agricultural module to the financial inclusion survey, unlike several surveys that cover mobile payment systems. From the 5 African countries covered in the survey, only three countries presented sufficient mobile money observations: Cote d'Ivoire, Tanzania, and Uganda. Due to a missing key, the Uganda survey was removed from the sample, leading to a final sample comprised of 6,175 households from Cote d'Ivoire and Tanzania. The households surveyed were farming dependent in terms of livelihood. They were identified on the basis of 9 criteria: market orientation, landholding size, labor input, income, farming system, farm management responsibility capacity, legal aspects and level of organization. Relying on responses from farming dependent households to understand mobile money usage allows us to relate mobile money usage decision to farming behavior, which is critical to investigate the mechanism through which mobile money affect market participation.

The Cote d'Ivoire sample covers three agricultural zones of the country: East Forest, West Forest, and Savanna. Of 3,333 households targeted by the survey, 3,019 were successfully interviewed in Cote d'Ivoire, resulting in an attrition rate of 9.42%. In Tanzania, 3,156 were initially targeted in 5 regions defined for the purpose of the survey: Border, Coastal, Inland, Lake, and Zanzibar. The interview was successfully conducted for 2,993 households out of 3,156, resulting in an attrition rate of 5.16%. In each household, an adult (age 15 and over) was randomly selected and surveyed among the active household members.

**Table 2.2** presents the summary statistics on key variables disaggregated by mobile money usage for commercial purposes. Mobile money users resemble their non-user counterpart to a large extent. Household heads aged on average 39 years among users, slightly younger than non-users. Household size averaged 5 members in both groups, each of which owned about the same area of land: 50 acres. Gender, years of education and farming experience of household heads were comparable across users and non-users sub-groups. Users were nonetheless slightly less experienced and more educated than their non-users counterparts. The most noticeable difference between the two groups relates to farming and marketing practices. A higher percentage of users were distant market participants, with a difference of 18 percentage points between the two groups. The other salient distinctive characteristic between users and non-users was the average monthly income earned by each household. Users monthly revenue exceeded non-users earnings by USD 44 on average, despite a slightly larger land area owned by non-users. However, the users' group was made of 13% more livestock owners than non-users. Cell phone ownership exhibits a small variation across groups, with only one cellphone owned on average in both groups. The users' group accounts for slightly more cell phone owners than the non-users group. Finally, major differences in geographic location were noticeable between the two groups. As expected, a higher proportion of urban households were mobile money users relative to rural households. Also, Cote d'Ivoire had a higher percentage of mobile money users than Tanzania.

**Table 2.2 Data summary statistics by mobile money usage**

| | Mean by mobile money usage | | | | |
|---|---|---|---|---|---|
| | Non-users | | Users | | Difference in |
| Variable | Mean | N | Mean | N | means |
| Selling to distant market | 0.39 | 1908 | 0.56 | 133 | -0.17*** |
| (dummy = 1 if true) | (0.01) | | (0.04) | | (0.04) |
| Male | 0.60 | 2378 | 0.65 | 170 | -0.05 |
| (dummy = 1 if true) | (0.01) | | (0.04) | | (0.04) |
| Education in years | 5.39 | 1742 | 5.96 | 130 | -0.57 |
| | (0.08) | | (0.32) | | (0.32) |
| Age | 41.17 | 2378 | 39.94 | 170 | 1.22 |
| | (0.29) | | (0.89) | | (1.09) |
| Household size | 5.21 | 2378 | 5.19 | 170 | 0.01 |
| | (0.06) | | (0.18) | | (0.22) |
| Income (US$ equivalent) | 126.92 | 2284 | 170.90 | 165 | -43.98*** |
| | (3.69) | | (32.05) | | (16.19) |
| Land size in acres | 51.94 | 2214 | 49.21 | 148 | 2.73 |
| | (1.3) | | (5.14) | | (5.19) |
| Years of farming experience | 11.02 | 2192 | 10.00 | 149 | 1.02** |
| | (0.11) | | (0.43) | | (0.43) |
| Cooperative membership | 0.08 | 2200 | 0.08 | 151 | 0** |
| (dummy = 1 if true) | (0.01) | | (0.02) | | (0.02) |
| Receive price information | 6.44 | 2200 | 10.43 | 151 | -3.99*** |
| (dummy = 1 if true) | (0.25) | | (1.14) | | (1.02) |
| Grow rice | 0.68 | 2214 | 0.75 | 148 | -0.07* |
| (dummy = 1 if true) | (0.01) | | (0.04) | | (0.04) |
| Owns livestock | 0.48 | 2214 | 0.61 | 148 | -0.13*** |
| (dummy = 1 if true) | (0.01) | | (0.04) | | (0.04) |
| Rural | 0.68 | 2378 | 0.52 | 170 | 0.16*** |
| (dummy = 1 if true) | (0.01) | | (0.04) | | (0.04) |
| Country | 0.57 | 2378 | 0.64 | 170 | -0.07** |
| (dummy = 1 Cote d'Ivoire) | (0.01) | | (0.04) | | (0.04) |
| Number of mobile phones | 1.13 | 2157 | 1.25 | 165 | -0.12*** |
| in households | (0.01) | | (0.03) | | (0.03) |

***, ** and * denote respectively significance at the 1%, 5% and 10% levels

Next, **Table 2.3** presents the summary statistics by distant market participation. A few patterns are worthy to be mentioned. Distant market participants and their non-participant counterparts share common demographics. Gender, Education, age and household size fall within the same value ranges across groups. As to farming practices, the two groups were made of similar proportions of cooperative members and livestock owners, with household heads averaging 11 years of farming experience in both groups. A larger share of distant market participants were mobile money users. The proportion of mobile money users among distant market participants is about twice the proportion of users among non-participants who resided for the most in rural areas. Surprisingly, non-participants owned on average 11 more acres of land than distant market participants. Figure 1 summarizes the main barriers to distant market participation reported by surveyed households. About 70% of the surveyed net seller farmers opting for local markets reported fear of opportunistic behavior from buyers as the main reason that motivates their local market choice.

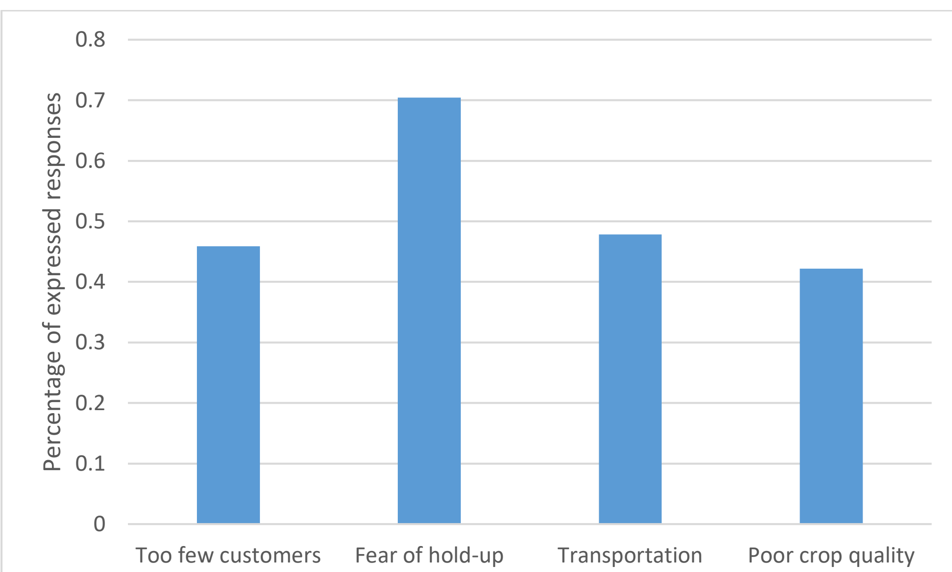


**Figure 2.1 Main reasons for opting for local markets**

**Table 2.3 Summary statistics by distant market participation**

| | By distance | | | | |
|---|---|---|---|---|---|
| | Local | | Distant | | |
| Variable | Mean | N | Mean | N | Difference |
| Mobile money | 0.05 | 1227 | 0.09 | 814 | -0.04*** |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.01) |
| Male | 0.58 | 2835 | 0.59 | 1753 | -0.01 |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.01) |
| Education | 4.53 | 1554 | 4.8 | 1060 | -0.26** |
| | (0.08) | | (0.1) | | (0.13) |
| Age | 42.09 | 2835 | 41.29 | 1753 | 0.80* |
| | (0.28) | | (0.35) | | (0.45) |
| Household size | 5.26 | 2835 | 5.47 | 1753 | -0.21** |
| | (0.06) | | (0.07) | | (0.09) |
| Income | 119.02 | 2680 | 112.73 | 1660 | 6.29 |
| | (4.53) | | (3.28) | | (6.31) |
| Land size in acres | 64.30 | 2835 | 52.74 | 1753 | 11.56*** |
| | (1.18) | | (1.4) | | (1.86) |
| Year of farming experience | 11.67 | 2783 | 11.17 | 1712 | 0.50*** |
| | (0.09) | | (0.12) | | (0.15) |
| Cooperative | 0.09 | 2798 | 0.07 | 1724 | 0.02 |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.01) |
| Receive price information | 5.40 | 2798 | 6.71 | 1724 | -1.31*** |
| (dummy = 1 if true) | (0.21) | | (0.29) | | (0.36) |
| Grow rice | 0.65 | 2835 | 0.69 | 1753 | -0.04*** |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.01) |
| Owns livestock | 0.44 | 2835 | 0.45 | 1753 | -0.01 |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.02) |
| Rural | 0.85 | 2835 | 0.76 | 1753 | 0.09*** |
| (dummy = 1 if true) | (0.01) | | (0.01) | | (0.01) |
| Country | 0.43 | 2835 | 0.48 | 1753 | -0.05*** |
| (dummy = 1 if Cote d'Ivoire) | (0.01) | | (0.01) | | (0.02) |
| Number of mobile phones | 1.11 | 1973 | 1.10 | 1279 | 0.01 |
| in households | (0.01) | 1227 | (0.01) | 814 | (0.01) |

***, ** and * denote respectively significance at the 1%, 5% and 10% levels

## Empirical analysis

From the mobile money incentive theory discussed above, it follows that the use of mobile money should affect market participation, especially distant and larger markets presenting apparent risks of hold-up. Ideally, a randomized control trial or other experimental design would allow us to estimate the average treatment effect (ATE) of mobile money on market participation. Since no such dataset is available, we rely on comparative non-experimental methods to test the hypothesis that mobile money increases distant market participation. Specifically, we carry out an empirical analysis using household-level data from a cross-sectional survey conducted in Tanzania and Cote d'Ivoire. In this section, we present our empirical models with their respective identification assumptions.

### Basic specification

We first conduct a reduced-form analysis to specify the relationship between distant market participation and mobile money. In this section, distant market participation $D_i$ by household *i* is measured by a discrete variable taking the value of one for sales in regional and local markets and zero for village market or farmgate sales. In the rest of the study, we will adopt the term "distant market" to allude to the regional and local markets which are generally characterized by higher prices and higher transaction costs associated with higher risks of hold-up. In the basic specification, farmers are assumed to be net sellers. Following the market participation model proposed by Alene et al. (2008), we describe the farmer market participation decision as follows:

$$D_i^* = \alpha T_i + \beta \theta_i + \varepsilon_i \qquad (3)$$

$$D_i = 1 \; if \; D_i^* > 0$$

$D_i^*$ is a latent variable function and $D_i$ a function taking the value of 1 for any positive value of $\alpha T_i + \beta \theta_i + \varepsilon_i$ and 0 otherwise. $T_i$ is a dummy variable indicating whether households receive payment from their customers through mobile money, and $\theta_i$ is a vector of demographic and socio-economic control variables comprising household size, income, land size, age, gender, years of education and farming experience of the household head as identified in the market participation literature (Alene et al., 2008; Bellemare and Barrett, 2006; Burke et al., 2015; Martey et al., 2017). We also included controls for livestock ownership, access to price information via cell phone, rice cultivation dummy for Cote d'Ivoire and Maize cultivation dummy for Tanzania as well as a country dummy.

**Identification**

To identify the causal link between mobile money and market participation, equation (3) requires the mobile money covariate to be exogenous. However, as mentioned in Jack and Suri (2014), mobile money adoption variables suffer from endogeneity due to selective adoption associated with social status or other unobservables. Indeed, one could argue that the use of mobile money to complete commercial transactions is simultaneously determined with the market participation variable by an underlying entrepreneurship factor. If the same unobserved variables impact mobile money use and market participation, any specification using the covariate "mobile money for commercial transaction" to identify the causal effect may lead to biased estimates. Jack and Suri (2014) and Munyegera and Matsumoto, (2016) use respectively the mobile money agent density within a specific radius of the household and the distance as an instrument for mobile money use. As the CGAP survey in Cote d'Ivoire and Tanzania does not contain any agent density data, we proxy agent density by households access to a mobile money agent within a walking distance from their house.  Then we construct a set of instruments that combines phone ownership, frequency of remittances and distance to a mobile money agent.

The instrument must satisfy two conditions: the exogeneity and the relevance conditions. The exogeneity of our instruments hinges on the argument that the set of instruments mainly affects market participation through mobile money. In addition to the distance proxy "access to a mobile money agent from a walking distance", we include the phone ownership and frequency of mobile money transactions to capture some variation in the mobile money activity in the households, given the cross-sectional data. Unlike the household status in terms of mobile money use, the frequency of mobile money transactions can be assumed not directly related to market participation, since mobile money transfers generally serve for a wide range of purposes including coping with financial hardships. One may argue that the frequency of remittances influence market participation through improved access to capital. However, the transfer amount is more likely to affect access to capital than the frequency of mobile money remittances. Moreover, given the seasonality of agriculture operations, agriculture-related remittances may not be completed frequently. Then the frequency of mobile money transfers carries some information about the frequency of market transactions completed through mobile money. By combining phone ownership, access to a mobile money agent and frequency of remittance, we put forward the argument that the resulting instrument does affect market participation through mobile money transaction incentives.

Next, we test the quality of the instrument under two criteria. We use the Kleibergen-Paap rk LM statistic to test for under-identification and the Cragg-Donald Wald F statistic to detect weak identification of the instrument with a standard 2 stage least square regression. The Lagrange Multiplier statistics (24.5) is higher than the Chi-square critical value at the 1% level of significance, leading to reject the null hypothesis of under-identification. The Cragg-Donald Wald F statistics is higher than the critical value for a 10% maximal IV relative bias. Then, we can expect less than 10% bias of the instrument. Finally, the Hansen J Statistics reveals over-identification. This is not surprising given the number of instruments that we include in this analysis. However, as emphasized by Parente and Silva (2012), over-identification tests can barely detect over-identification of the set moment conditions implied by the economic model. We rely on the economic rationale described above to assert the validity of our instruments.

**Binary endogenous regression models**

***Bivariate Probit model***

The dependent variable market participation $D_i$ and the endogenous covariate mobile money $T_i$ are both binary variables. Common two-stage least square (2SLS) estimation such as (2SLS) linear probability model (LPM) or control function approaches such as the ivprobit command of stat presents important flaws pointed out in Lewbel et al. (2012), mainly because they lead to inconsistent or biased estimates when the endogenous regressor is binary. We first employ a recursive bivariate probit model (RBP) in the empirical analysis as in Ma et al. (2018) and Bontemps and Nauges (2016). The RBP is a maximum likelihood estimator that permit general form of heteroskedasticity. The model consists of equation (3) to which we add a second equation (4) with a latent variable function describing the decision of mobile money use as following:

$$T_i^* = \delta\theta_i + \gamma Z_i + \mu_i \tag{4}$$

$$T_i = 1 \; if \; T_i^* > 0$$

where $Z_i$ is an instrument and $\mu_i$ the error term. $\theta_i$ is the vector of demographic and socio-economic variables defined in (3). A required assumption to the estimation of the bivariate probit model is that the error terms $(\varepsilon_i, \mu_i)$ follow a bivariate normally distributed (Wooldridge, 2011). Additionally, the RBP model requires the relationship in (4) to be correctly specified, that is $Z_i$ should feature a complete set of instruments. The direct implication of the specification assumption is the relevance of the instrument.

***Special regressor approach***

The bivariate probit model discussed above constitute a valid alternative to the LPM and control function approaches but makes strong distributional and functional form assumptions (Wooldridge, 2011). The special regressor approach proposed by Dong and Lewbel (2015) requires weaker assumptions mainly hinging on the exogeneity of the variable used as special regressor. Specifically, the special regressor must be conditionally independent of $\varepsilon_i$ and distributed with large support. The special regressor resolves the issues raised by likelihood estimators such as bivariate probit since it allows for unknown forms of heteroscedasticity and consistently estimates the endogenous variable coefficient (Lewbel, revised April 2011). We exploit this approach to estimate another model of the relationship between the binary endogenous regressor mobile money and the binary dependent variable market participation, as in Bontemps and Nauges (2016) and Ruyssen and Salomone (2018). The model specification is a revision of equation (3) to include a new variable $S$ called special regressor, as follows:

$$D_i^* = \alpha T_i + \beta \theta_i + S_i + \varepsilon_i \tag{5}$$

$$D_i = 1 \; if \; D_i^* > 0$$

As mentioned above, the special regressor $S$ must be unrelated to the covariates in equation (3), while expected to affect our outcome market participation. In this study, we exploit the 2015 rainfall deviation from 30 years average in the wet season in Cote d'Ivoire and Tanzania. To demonstrate the relationship between rainfall deviation and market participation, we put forward the argument that high deviations from rainfall averages rainfall are supply-shifters that induce high price variability, affecting participation in distant markets. The positive relationship between rainfall deviation and market prices is demonstrated in Barrios et al. (2008) and Sassi and Cardaci (2013).

To construct the rainfall deviation variable, we first obtain satellite rainfall data from the African Rainfall Climatology, version 2 (ARC2) of the National Oceanic and Atmospheric Administration (NOAA) (Novella and Thiaw, 2012). The dataset contains gridded daily precipitation estimates of the African continent from 1983 to 2019. The spatial resolution of 10km x 10 km (0.1-degree grid) is precise enough to provide rainfall estimates of the geographic location of the households included in the survey. We use the Google Maps geocoding API (Python) to match the household location to their corresponding precipitation levels based on their geographic coordinates. The computed special regressor consists of the 2015 rainfall deviation from the 1995 to 2014 average over the wet season in Tanzania and Cote d'Ivoire.

The rainfall deviation is continuously distributed with large support. Indeed, Lewbel et al. (2012) assert that any normally distributed variable should satisfy the condition of common support. We expect the rainfall deviation to affect positively prices through resulting lower yields. Since higher prices drive market participation up, we expect a positive relationship between rainfall deviation and market participation; then the $E(D \mid T, \theta, S)$ increases with rainfall deviation (S).

We compute the marginal effects of each covariate in the special regressor model following Lewbel and Yang (2012). The marginal effects represent the derivative of the average index function $V(X'\beta + S) = E(D|X'\beta + S)$, expressed as follows:

$$\frac{\partial E(D|X'\beta + S)}{\partial X} = v(X'\beta + S)\beta \tag{6}$$

The estimates of the marginal effects are given by:

$$\bar{v}\hat{\beta} = \frac{1}{n}\sum\nolimits_{i=1}^{n} \hat{v}_i\hat{\beta} \tag{7}$$

where $\hat{v}_i$ is an estimator of the average index function $v_i$ as in Lewbel and Yang (2012).

## Results and discussion

We present the estimates of the recursive bivariate probit (RBP) (model 1) and the special regressor (SREG) (model 2) models that we compare to the Instrumental Variable Probit (IVprobit) (model 3) in **Table 2.4**. As described above, the main model consists of two equations: the market participation equation (3) and the mobile money equation (4). The first two models assume a binary mobile money dependent variable $T_i$ , while in the IVprobit model, $T_i$ is required to be continuous. The RBP and SREG models should provide the most consistent estimates since they handle better endogenous binary regressor (Wooldridge, 2011). **Table 2.5** reports the marginal effects of the set of covariates on market participation for the three models. The analysis indicates that the variable mobile money is endogenous. In all three models, the instrument consists of three variables: mobile phone ownership, presence of a mobile money agent within a walking distance from home, and the average monthly frequency of remittances over the last three months preceding the survey. In model (2), the special regressor consists of the 2015 rainfall deviation from a 30 years' average over the wet season. The estimation results in all three models show a positive and significant effect of mobile money on market participation with a higher magnitude of the mobile money coefficient estimate in model (3). In addition, the estimation of the three models consistently reveals a significant relationship between the dependent variable market participation and the covariate *rainfall deviation* and *land size*.

**Table 2.4 Estimates of the three models, main specifications (Standard errors in Parentheses)**

| Dependent variable: **Market participation** | **Bivariate probit** | **Special regressor** | **IV probit** |
|---|---|---|---|
| Mobile money | 1.255*** | 1.168** | 0.454*** |
| | (0.449) | (0.461) | (0.152) |
| Rainfall deviation | 0.246** | | 0.089** |
| | (0.113) | | (0.041) |
| Household size | 0.028*** | 0.000 | 0.010*** |
| | (0.010) | (0.005) | (0.004) |
| Male | 0.083 | 0.018 | 0.030 |
| | (0.061) | (0.032) | (0.022) |
| Age | -0.007 | -0.006 | -0.002 |
| | (0.011) | (0.006) | (0.004) |
| Age squared | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| Land size | -0.002*** | -0.001*** | -0.001*** |
| | (0.001) | (0.000) | (0.000) |
| Rural | -0.262*** | -0.037 | -0.095*** |
| | (0.068) | (0.038) | (0.025) |
| Tanzania | 0.053 | -0.163*** | 0.019 |
| | (0.066) | (0.036) | (0.024) |
| N | 2041 | 1939 | 2041 |
| Log-likelihood | -1800.53 | | -1343.80 |

*, **, ** denote significance at the 1%, 5% and 10% levels.

***Bivariate Probit***

To determine whether the mobile money variable is endogenous, we first estimate a seemingly unrelated bivariate probit model (SUBP) by excluding mobile money from the market participation equation following Ma et al (2017) and Thuo et al (2014). If mobile money is correlated with market participation through unobserved heterogeneity, we will conclude that mobile money is endogenous. The LR test of the hypothesis $\sigma = corr(\mu_i', \varepsilon_i) = 0$ yields a chi-square statistics of 10.53, higher than critical chi-square (1 degree of freedom at the 5% significance level). In both models (SUBP and RBP), we reject the null hypothesis of zero correlation and conclude that the mobile money variable is endogenous. This justifies the use of the RBP model to estimate the effect of mobile money on market participation.

Next, we assess the goodness-of-fit of the RBP model and the joint normal distribution of the error terms using respectively the Hosmer-Lemeshow goodness-of-fit (Hosmer and Lemesbow, 1980) and the Murphy score (Murphy, 2007) tests proposed by (Chiburis, 2011). The chi-square statistics of the Hosmer-Lemeshow test is 20.22, higher than critical chi-square (21 degree of freedom at the 5% significance level). We fail to reject the null hypothesis of misspecification on the Hosmer-Lemeshow, implying that the model is correctly specified. Yet, the null hypothesis of joint normal distribution of the error terms is rejected at the 5% level. This suggests bias in the parameter estimates due to notable skewness and Kurtosis.

The estimated marginal effects of the RBP (Left panel of **Table 2.5**) show that using mobile money increases the likelihood of market participation by 45 percentage points on average. This result is consistent with the prediction of the theoretical model. The RBP model yields a mobile money estimate of more than five folds lower than the estimate of the IV probit model. This is not surprising since the IV probit assumes a linear mobile money equation. As a result, we may observe values of the mobile money estimates out of the range (0, 1) in the IV probit model. These discrepancies between IV probit and binary endogenous covariate estimation methods such as RBP and Special regressor are stressed in Dong and Lewbel (2015) and Bontemps and Nauges (2016).

**Table 2.5 Estimated marginal effects (Standard errors in Parentheses)**

| Dependent variable: **Market participation** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| | **Bivariate probit** | | **Special regressor** | | **IV probit** | | **OLS** | |
| Mobile money | 0.4537 | *** | 0.5513 | ** | 2.6086 | *** | 0.1556 | *** |
| | (0.1522) | | (0.2530) | | (0.5945) | | (0.0434) | |
| Rainfall deviation | 0.0890 | ** | 0.5121 | *** | 0.2324 | ** | 0.0889 | ** |
| | (0.0408) | | (0.0920) | | (0.1081) | | (0.0432) | |
| Household size | 0.0103 | *** | 0.0025 | | 0.0239 | ** | 0.0108 | *** |
| | (0.0037) | | (0.0032) | | (0.0102) | | (0.0039) | |
| Male | 0.0300 | | -0.0042 | | 0.0536 | | 0.0352 | |
| | (0.0221) | | (0.0208) | | (0.0597) | | (0.0229) | |
| Age | -0.0024 | | -0.0030 | | -0.0094 | | -0.0019 | |
| | (0.004) | | (0.0034) | | (0.0104) | | (0.0041) | |
| Age squared | 0.0000 | | 0.0000 | | 0.0001 | | 0.0000 | |
| | (0.0000) | | (0.0000) | | (0.0001) | | (0.0000) | |
| Land size | -0.0007 | *** | -0.0004 | ** | -0.0017 | *** | -0.0007 | *** |
| | (0.0002) | | (0.0002) | | (0.0005) | | (0.0002) | |
| Rural | -0.0945 | *** | 0.0022 | | -0.1665 | ** | -0.1141 | *** |
| | (0.0249) | | (0.0258) | | (0.0809) | | (0.0246) | |
| Tanzania | 0.0190 | | -0.0827 | *** | -0.0066 | | 0.0320 | |
| | (0.0241) | | (0.0237) | | (0.0676) | | (0.0244) | |
| N | 2041 | | 1843 | | 2,041 | | 2041 | |

*, **, ** denote significance at the 1%, 5% and 10% levels

Other significant variables include deviation from rainfall average, household size, land size and location in a rural area. The variables all have the correct signs. A positive or negative deviation from rainfall average may lower crop yields and affect the supply of products on crop markets. As a result, we should expect prices to increase and markets to attract more farmers. As in Martey et al. (2017), larger households are found to participate more in distant markets than their smaller counterparts. Specifically, an additional household member increased the probability of market participation by 1 percentage point. The two negative coefficients are respectively "land size" and "rural". The negative sign of land size in models (1) and (3) may appear counterintuitive since we expect large landowners to participate more in distant markets to sell their marketable surplus. However, we should not ignore that larger lands mostly host cash crops wholesaled to agribusiness firms and/or cooperatives, including export crops such as cocoa and coffee in Cote d'Ivoire and cotton and coffee in Tanzania. The spot markets alluded to in this study are known to host transactions involving smaller quantities of products. Hence it is not uncommon to expect land constrained farmers to participate more in spot market transactions. Finally, as expected, farmers living in rural areas are less likely to participate in distant markets, consistent with findings in Burke et al. (2015).

***Special Regressor***

In using the special regressor approach, we first construct the variable identified as special regressor. This variable consists of the rainfall deviation from 30 years average as in (Amare et al., 2018). It satisfies the requirements of continuous distribution with large support, then can be assumed exogenous. The Breusch-Pagan test of heteroscedasticity on the regression of S on the other covariates reveals the presence of heteroscedasticity. The null hypothesis of homoscedasticity is rejected the 1% level of significance. We thus allow an unknown form of heteroscedasticity in our model. We use a kernel density estimator of the residuals density function in the first step of the special regressor estimation, with a standard Epanechnikov kernel function. A 95% trimming is applied to the sample as in Bontemps and Nauges (2016). Panel 2 of **Table 2.5** presents the estimated marginal effects of the special regressor model, computed as described above.

Farmers using mobile money are more likely to participate in distant markets by a 55 percentage point. The special regressor provides a slightly larger estimate of the marginal effect of mobile money relative to the RBP. In both models, the magnitude of this effect ranges between 0 and 1, as opposed to 2.6 with the IVprobit estimation. The larger magnitude of mobile money estimate relative to the other covariates in all three models leads us to acknowledge the critical role that mobile money can play in market participation decisions. Previous studies have found a positive effect of mobile money on welfare (Munyegera and Matsumoto, 2016) without necessarily testing the mechanism through which mobile money affects welfare. An exception is found in (Jack and Suri, 2014). The results of our study not only confirm this positive effect on welfare but also sheds light on one of the potential channels through which mobile money can affect welfare.

The rainfall deviation variable is positive and statistically significant in the three specifications, despite a higher magnitude in the special regressor model. The rainfall deviation estimate shows a positive price effect on market participation, comparable to the mobile money effect in the special regressor estimation. The remaining covariates affect market participation to a lesser extent than mobile money and rainfall deviations. For example, the land size had a significant but small effect on market participation. From the special regressor model estimates, it appears that Tanzanian farmers are less likely to participate in distant markets than their Ivorian counterparts.

***Levels of market participation***

In line with the theoretical model, we expand the analysis to investigate whether the mechanisms provided by mobile money leads farmers to participate in markets carrying the higher risks of hold-up. It is well accepted that the threat of hold up increases with the distance or the size of the market (Figure 1). First, we rank 4 markets by the importance of the hold-up threat: farm gate (1), village (2), local market (3) and regional market (4). Farm-gate represents the venue with the lowest threat of hold-up since farmers incur fewer transaction costs as defined in the theoretical model section. The threats of hold-up are the most prominent on the regional markets given the higher transaction costs (transportation, negotiation, enforcement) that each farmer must incur to successfully complete a transaction.

The ordered nature of the new dependent variable market participation (1-4) requires an ordinal model to estimate the effect of mobile money and other control variables. We use an ordered probit model with the same control variables as in equation (4). Due to the dataset limitations and computational issues, we do not use an instrument for mobile money in the ordered probit specification but rather the use of mobile money to receive payment from customers (T). We acknowledge the potential endogeneity that may bias the estimates but we are mainly interested in a comparison of mobile money estimates across market levels rather than the magnitude of the estimate per se. The results of the analysis show that market participation increases with the importance of the threat for mobile money users (**Table 2.6**), which leads to conclude that the mobile money may play a critical role in alleviating the uncertainty around the transaction on distant, more important markets.

**Table 2.6 Marginal effects of the ordered probit model at means**

| Market | Mobile Money = 0 | (SE) | Mobile money = 1 | (SE) | Change |
|---|---|---|---|---|---|
| On farm or to traveling merchant | 0.11*** | (0.01) | 0.07*** | (0.02) | -0.04** |
| At village | 0.44*** | (0.01) | 0.38*** | (0.08) | -0.05** |
| At local market | 0.40*** | (0.01) | 0.48*** | (0.03) | 0.08** |
| At regional market | 0.04*** | (0.01) | 0.07* | (0.01) | 0.02** |

***, ** and * denote respectively significance at the 1%, 5% and 10% levels

We conduct additional robustness checks using alternative model specifications and additional control variables. The results are consistent across specifications (Appendix A).

# Conclusion

Since the mobile money revolution in Kenya, there is an increasing interest in understanding its potential effects on vulnerable communities in developing countries. If a growing body of work points out the role played by digital payments in improving various dimensions of welfare, the mechanism through which mobile may impact welfare has received scant attention from the empirical literature. As a result, most studies consider the remittance pathway as the most plausible mechanism through which mobile money may impact welfare.

We develop and test a conceptual model based on a transaction costs economics framework to explain how digital payments improve market participation. Our empirical approach consists of the special regressor method that efficiently addresses the endogeneity of the binary variable of interest – that is, mobile money. We find that the probability of distant market participation is increased on average by 55 percentage points for mobile money users. Furthermore, we rank marketing venues based on hold-up risk and find that the effect of mobile money is the most prominent on decisions to switch from village to local market. Our study adds to the literature by establishing support for the existence of a third pathway through which mobile money may impact welfare and market participation. To date, this is the first study to utilize a transaction cost economic framework to explain the positive welfare effect of mobile money.

The results of the analysis conducted on Cote d'Ivoire and Tanzania data indicated demonstrate how farm and non-farm enterprise owners would benefit from the spread and accessibility to digital payments beyond the traditional pathway of credit, savings, and remittances. By cutting down the substantial transaction costs that preclude market participation, digital payments offer an innovative solution for addressing market failures due to high transaction costs. In addition, the large scale adoption of the technology which is demand-driven, unlike numerous interventions in rural areas, suggests sustainable impacts.

If the findings of the study hold for Cote d'Ivoire and Tanzania, a number of factors should be considered when generalizing the implications to a wider sample of Sub-Saharan African countries. Differences in literacy, fiscal policy, cell-phone ownership and other factors that affect the use of mobile money may also affect the extent to which mobile money addresses market failures. One other caveat to the optimistic conclusion of the results is that our sample includes only a limited number of mobile money users (less than 10%). Moreover the dataset includes few details about the transaction. Our variable of interest does not distinguish users that receive payment for sale of agricultural products from users that are paid for services or products from non-farm enterprises. This has important implications on the set of possible market choices by the surveyed households.

Although mobile money may affect market participation in general, the effect of mobile money on the quantity of product sold is unknown. Moreover, our results provide no insight into the welfare gain attributed to the transaction costs pathway of mobile money. This research points out a need for quantifying the gains in revenues for different types of transactions and household categories. This seems a fertile area for further research.

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# Chapter 3 - Mobile money and household resilience: A development resilience approach

## Introduction

Poor and resource-constrained rural households in developing countries are particularly vulnerable to the negative effects of income shocks associated with natural hazards, disease, unexpected social hardships, and price volatility in input and output markets. Negative income shocks exacerbate the risk of food insecurity already prominent in most rural communities of Sub-Saharan Africa, whose livelihood depends primarily on agriculture. It is therefore critical for vulnerable households to adopt efficient risk management strategies. In developed countries, farmers have access to credit, insurance and other services that protect them against most shocks. Unfortunately, inexistent or poor access to insurance in developing countries force rural households to underinvest in risk management strategies that would provide access to or sustain food security during periods of hardship (Banerjee and Duflo, 2007). Instead, they tend to rely on livelihood threatening strategies such as selling productive assets to offset consumption shortfalls when facing a negative shock (Fafchamps et al., 1998). While such a strategy may provide short-term relief in times of hardship, it clearly diminishes households' capacity to cope with future shocks. Consequently, policymakers and development communities are in a continuous search for mechanisms designed to enhance the resilience of smallholder agricultural producers in developing countries.

There is empirical evidence that social networks could offer an alternative to formal insurance markets (citations). Studies indicate that numerous rural communities in Africa utilize a system of informal insurance based on loan exchange. Udry (1990) and Weerdt and Dercon (2006) have illustrated the positive effects of informal insurance networks in Africa.

Nonetheless, rural households remain vulnerable to shocks because social networks are limited in size and magnitude of exchanges. It has been shown that the size of a social network decreases with the cost of establishing and coordinating relationships while the magnitude of exchanges falls with monitoring and enforcement costs (Murgai et al., 2002). These two categories of transaction costs may increase in magnitude with the distance between members of a social network since remoteness increases the risks associated with the coordination and enforcement of informal contracts. This risk is also exacerbated by the high cost of money transfers between distant members of a social network. Traditional money transfer methods at the local scale include physical transfer in person, using a bus driver or a money transfer service such as Western Union (Economides and Jeziorski, 2017), all of which entail high costs.

Recent large-scale adoption of mobile technologies has unleashed new perspectives of cheaper money transactions for rural households receiving remittances. One of these technologies, mobile money was introduced in Kenya in 2007 by Safaricom (M-PESA) and was widely adopted since. In addition to being faster than traditional remote money transaction methods, mobile money entails a significantly lower cost of sending and receiving money. The positive effect of mobile money on consumption smoothing is demonstrated in Kenya (Jack and Suri, 2014) and Uganda (Munyegera and Matsumoto, 2016). However, there is little evidence of potential effect of mobile money on long-run food security and resilience. Most of the studies in the literature to date that have investigated the relationship between mobile money and welfare rely on static measures of welfare.

The purpose of this study is to investigate the impact of improved risk-sharing through mobile money on farmers' resilience, using alternative measures of resilience. Improved ability of the households to withstand and recover from unexpected income shocks is likely to result in long-term positive effects. While Jack and Suri (2014) establish a solid case on the direct effect of mobile money on consumption, it is without surprise that this pioneering study found no effect of mobile money on wealth when measuring the outcome of interest on the basis of a static monetary value of assets. In this study, we use a forward-looking approach grounded on the development resilience to investigate the impact of mobile money on resilience.

### Development resilience

The word “Resilience” derives from the Latin term *resilire*, meaning "to jump back" or "to recoil" (Fan et al., 2014). In the development arena, the concept of “resilience” is perceived as a normative goal toward which policymakers, non-profit organizations, and researchers develop their projects. Although no clear consensus exists around the definition of resilience, this concept is usually perceived as the ability to deal with adverse changes and shocks (Béné et al., 2012). The growing interest in this concept stems from its holistic framework that allows researchers and anti-poverty programs to understand the relationship between a myriad of stressors faced by the poor and key well-being indicators. Particularly, resilience integrates three key notions: the well-being dynamics, the critical role of risk, and the connection between economic, social and environmental factors that affect peoples’ lives (Barrett and Headey, 2014). Economic variables are made of global market forces rendering prices volatile and impeding access to food, while environmental factors include natural disasters and climate change-related risks and social threats to resilience consist of conflicts and social instability. Resilience is attractive as a framework. Yet its measurement presents multiple challenges related to the complexity and dynamics that characterize well-being in populations facing shocks (Knippenberg et al., 2019).

In an attempt to reconcile definition and measurement, Barrett and Constas (2014) develop the concept of "development resilience" that recognizes and emphasizes three features: individual-level well-being measurement that can also be aggregated, indicator that integrates the effect of stressors and risks, and measurement that accounts for wellbeing dynamic path. Barrett and Constas (2014) conceptualize development resilience as "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks". As a result, a household is qualified as resilient if its capacity to avoid poverty "remains high over time".

The measurement of development resilience proposed by Barrett and Constas (2014) is based on a stochastic well-being outcome, $W$ , that represents the state of an individual or a community. The dynamic well-being of the individual of interest is described by a set of moment functions $m^k(W_{t+s}|W_t, \varepsilon_t)$, where $m^k$ denotes the $k^{th}$ moment, notably the mean ($k = 1$), the variance ($k = 2$), or the skewness ($k = 3$). Specifically, $m^k$ is a conditional moment describing the well-being state $W_{t+s}$ in period $t + s$ conditional on the well-being state in period $t$. The set of conditional moments characterizes the distribution of possible well-being states of the individual or community. The development resilience approach has led to an emerging body of literature on targeting or impact evaluation methodology in vulnerable community settings (Cissé and Barrett, 2018; Knippenberg et al., 2019; Phadera et al., 2019). One interesting feature of this approach is to allow for nonlinear well-being path dynamics, consistent with the theory of poverty traps. In fact, the Barret and Constas (BC) approach is derived from the poverty traps literature.

In the context of poor households, one assumption made to test the existence of poverty traps, particularly asset-based poverty traps, is poor households' exclusion from credit markets (Barrett and Carter, 2013). In such conditions, households below the Micawber threshold – the level of asset under which a household finds no longer attractive or feasible to pursue an asset accumulation strategy (Zimmerman and Carter, 2003) - are trapped into poverty. However, if this binding credit constraint is relaxed by digital payments that improve the financial inclusion of poor households, there are reasons to think that these technologies can contribute to building resilience. Relying solely on a first moment outcome would not allow us to capture the dynamics induced by the improved access to credit markets, especially an outcome that results from an asset accumulation strategy. The development resilience approach that allows various shocks and stressors to impact resilience is suited to evaluate the impact of shocks on long-run well-being outcomes (Phadera et al., 2019).

## Theoretical model

### Theoretical foundations on consumption smoothing

To derive the testable hypotheses, we start by laying out Deaton (1991)'s canonical model of optimal intertemporal consumption behavior (Carter and Lybbert, 2012). In this model, an individual that is rationed out of credit markets, and receives a stochastic income stream maximizes the utility function:

$$\max_{\{c,A\}} \left\{ \sum_{t=0}^{\infty} \left( \frac{1}{1+\delta} \right)^{t} v(c_t) \right\} \tag{8}$$

subject to:

$$x_t(\theta, A) = G(\theta_t) + (1+r)A_t \tag{9}$$

$$c_t \leq x_t \quad \forall t \tag{10}$$

$$A_{t+1} = x_t - c_t \tag{11}$$

$$A_{t+1} \geq 0 \tag{12}$$

where $c_t$ is the consumption in period $t$ and $A_t$ is the individual's current productive asset stock. The labor income $y_t = G(\theta_t)$ earned by the individual and the return on productive assets at the rate $r$ yield $x_t$, defined as cash-on-hand in the first constraint (9). The labor income $G(\theta_t)$ is a function of the random variable $\theta_t$. Constraints (10) guarantees that consumption in period t does not exceed the value of cash-on-hand. In constraint (11), the remaining value of cash-on-hands after consumption in period $t$ is carried out in the next period $(t + 1)$ as asset stock. The non-negativity constraint (12) ensures that the borrowing constraint is satisfied. Deaton (1991) assumes in his model that labor is inelastically supplied.

For an impatient individual that values more current consumption than future returns to assets, $\delta > r$. The optimality condition requires that consumption in periods $t$ and $t + 1$ satisfies the Bellman equation:

$$v'(c_t) = max\{v'(x_t), \beta E_t[v'(c_{t+1})]\} \tag{13}$$

where:

$$\beta = \frac{1 + \delta}{1 + r} > 1 \tag{14}$$

Deaton's model can be used to describe the choices of a borrowing-constrained individual facing an income shock under two scenarios.

Scenario 1:

$$v'(x_t) < \beta E_t[v'(c_{t+1})] \tag{15}$$

When the discounted expected marginal utility next period exceeds the marginal utility of current consumption $x_t$, the individual facing independent and identically distributed (iid) shocks will pursue a consumption smoothing strategy that consists of selling units of assets $A_t$.

Scenario 2:

$$v'(x_t) > \beta E_t[v'(c_{t+1})] \tag{16}$$

This scenario is more likely to occur when cash-on-hands drops to the point where the marginal utility of consumption is lower than the marginal utility of assets. Deaton's model predicts a reduction in consumption but also in cash on hands in the long run.

Under both scenarios, a consumption smoothing strategy is pursued at least to some extent in the long run. Now let's assume that the individual facing a random shock is a mobile money user and that the anticipated reduced consumption after shock is $\omega$, with $\omega_t < c_t$. As a result, the individual reduces his cash-on-hands by $\lambda$ ($\lambda > 0$) which implies a reduction of the asset stock $A_t$ for a sufficiently severe shock. Risk-sharing through mobile money could restore consumption to a level above $\omega_t$ as demonstrated by Jack and Suri (2014)'s following model of risk-sharing.

*Risk Sharing model*

In the risk-sharing model, we consider two additional individuals who share a mutual insurance network with the consumer in (10). The three individuals $i \in \{1, 2, 3\}$ are assumed identical, earning each $y_{it}$ in period $t$. As a starting point, let's consider the case of no-cost transfer. Assuming risk-averse individuals and income variability as the only source of uncertainty, the utility maximization problem of individual $i$ required by a Pareto efficient consumption plan across states can be described as following:

$$\max_{c_{1t}, c_{2t}, c_{3t}} \sum_i u(c_{it}) \tag{17}$$

subject to:

$$\sum_i c_{it} = 1 \text{ for each } t. \tag{18}$$

*Money transfer at no cost*

When total income in each period is shared equally, the optimal allocation of consumption is characterized by two money transfers in any possible direction. Either one individual receives a money transfer from the two other individuals or one individual transfers money to the two others. The resulting ex-post welfare at no cost transfer is depicted in Figure 1 (Panel A) and expressed as follows:

$$\pi^* = 3u\left(\frac{1}{3}\right) \tag{19}$$

*Money transfer at cost $\tau$*

Transaction costs are inherent to any method of money transfer including through formal institution or informal carrier. When a fixed cost $\tau$ is applied to each transaction among respective pairs of individuals, with $\tau > 0$, the solution to the utility maximization problem leads to three alternative levels of ex-post welfare:

$$\pi \in \left\{\sum_{i=1}^{3} u(y_i),\ u(y_1) + 2u\left(\frac{1 - y_1 - k}{2}\right), 3u\left(\frac{1 - 2k}{3}\right)\right\} \tag{20}$$

The first welfare level $A_0 = \sum_{i=1}^{3} u(y_i)$ characterizes a scenario of no transfer realization, while $A_1 = u(y_1) + 2u\left(\frac{1-y_1-k}{2}\right)$ describes the ex-post welfare associated with one transfer from any of the individual to another, and the welfare level $A_2 = 3u\left(\frac{1-2k}{3}\right)$ is reached with two transfers occurring between any pair of individuals and the third one. The areas of the simplex in Figure 3.1 (Panel B) correspond to each level of ex-post welfare. With the transfer cost $\tau$, decisions to transfer money are constrained by the magnitude of $\tau$. Income differentials should, therefore, be large enough to allow any transfer, which increases the occurrence of $A_0$ and $A_1$.

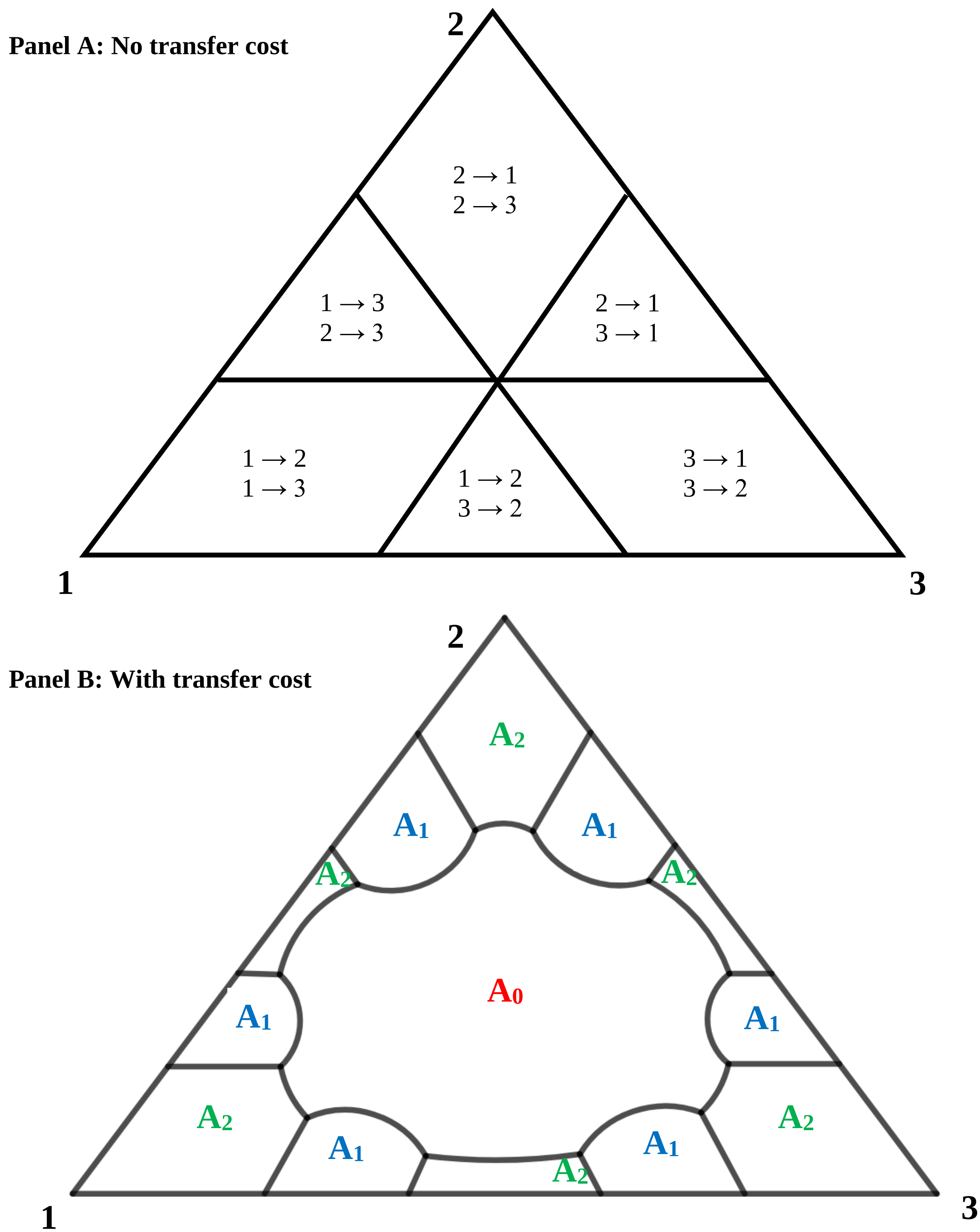


**Figure 3.1 Ex-post welfare**

The reduction in the cost of transferring money $\tau$ shrinks the areas $A_0$ and $A_1$ and increases the occurrences of a two-transfers scenario $(A_2)$. It follows from the model above that each individual of the network is better off with a reduced cost of risk-sharing. A low-cost money transfer service such as Mobile Money is likely to increase the number of active network participants and the number of transactions in the network. The direct implication for consumer $i$ is to reach a new consumption level $q$ above anticipated reduced consumption $\omega_t$ after the shock $(q_t > \omega_t)$. Because the marginal utility is assumed monotonically decreasing, $\beta E_t[v'(q)] < \beta E_t[v'(\omega)]$. As a result, the intensity of asset depletion $\Delta x$ required to raise the marginal utility of cash-on-hands to $\beta E_t[v'(q)]$ is lower than the level of asset depletion $\Delta x'$ necessary to reach $\beta E_t[v'(\omega)]$ under scenario 1 in (15). Scenario 2 yields the same prediction as scenario 1 for a shock sufficiently strong to raise $\beta E_t[c'(q)]$ above the marginal utility of assets.

### Alternative coping strategies

Consumption smoothing is not the only risk coping mechanism adopted by rural households. Empirical evidence suggests that poor households alternatively adopt asset smoothing strategies (Fafchamps et al., 1998; Kazianga and Udry, 2006; Verpoorten, 2009). One limitation of Deaton's model is to not fully account for such alternatives. In this vein, Carter and Lybbert (2012) demonstrate the coexistence of consumption and asset accumulation strategies by describing and empirically testing a poverty trap model. However, this should not alter the prediction of the theoretical model in the context of the study. We mainly focus on shocks described as intense by the surveyed households. These shocks are more likely to draw borrowing-constrained households to lower their asset holdings even under an asset smoothing regime.

From the theoretical model above, it follows that risk-sharing through mobile money improves household resilience to intense negative shocks through an increased number of network participants and transactions.

## Empirical investigation

### Identification

A credible methodological approach to evaluating the impact of mobile money adoption on household resilience would require a valid counterfactual, that is a comparison group that resembles the mobile money users in observable and unobservable characteristics, with the deviating factor being the use of mobile money. One could arguably refute that Kenyan households randomly adopt the mobile payment technology, leading to a self-selection issue. Additional socioeconomic variables including income could affect mobile money adoption decisions, such variables having a non-stochastic relationship with our outcome of interest. Our identification approach hinges on the use of the distance to the nearest mobile money agent as an instrument for mobile money use to address the potential self-selection issue. Technically, the approach will allow us to estimate the effect of mobile money on resilience based on the assumption that improved access to mobile money leads to increased use of the service. This is a reasonable assumption since the correlation test show a relative strong negative correlation between distance to the nearest mobile money agent and mobile money use.

One criticism of the use of the distance as a proxy for mobile money access stems from the potential non-randomness in the mobile money agent roll-out in Kenya. If the mobile money agent distribution network is uncorrelated to the household characteristics over the period running from the lunch of M-PESA in Kenya (2008) to the second survey round (2009) (Jack and Suri, 2014), we could hardly make the case that any further agent network development plan is irrelevant to the households' income level or other socio-demographic variables. Agent networks may expand faster in wealthier neighborhoods. However, mobile money retailing may equally flourish in poorer neighborhoods, where households are more prone to receive remittances from their distant relatives or acquaintances. Figure 2 maps the relationship between distance to the nearest agent and asset ownership over the 4 rounds of the survey. The plot shows no apparent relationship between the agent distribution network and household well-being levels, though a large proportion of surveyed households are within 5 km of an agent location.

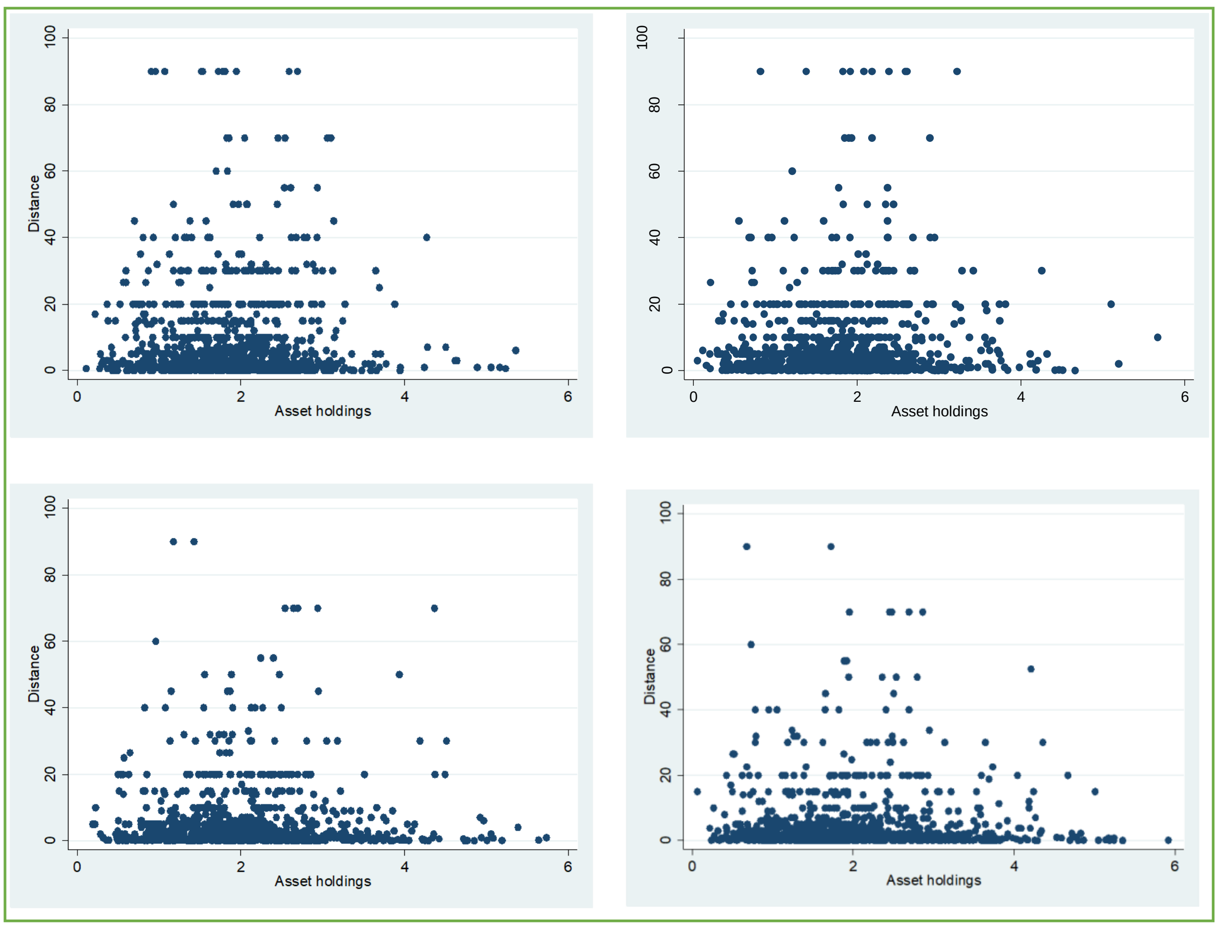


**Figure 3.2 Distance to the nearest mobile money agent by levels of asset holding**

To confirm the stochastic relationship between distance to the nearest agent and wealth, we perform a mean difference comparison. P-values are respectively 0.9542, 0.3547, 0.4116 and 0.9848 for survey rounds 1, 2, 3 and 5, supporting the claim that the agent positioning is irrelevant to the population level of wealth.

## Construction of the asset-based well-being index

The outcome variable consists of a measure of resilience based on productive asset ownership. The main challenge to estimating an asset-based measure of well-being in dynamic settings is the dimensionality problem as stressed by Barrett and Carter (2013). Because households own a portfolio of multiple assets, comparing well-being across heterogeneous households becomes problematic. As a result, the majority of studies that deal with dynamic asset-based measures of well-being are conducted in pastoralist settings where household livelihoods heavily depend on livestock holdings (Cissé and Barrett, 2018; Lybbert et al., 2004; Phadera et al., 2019). Our study population consists of households from all regions of Kenya, which implies a diversity of livelihood strategies and productive asset portfolios among surveyed households. Thus, the construction of a valid multi-asset index is critical to address the dimensionality problem and properly capture the effect of the variable of interest.

We construct a Livelihood-Weighted Asset Index (LWAI) as in Adato et al. (2006), where the asset index $LWAI(A_{it})$ is a one-dimension measure of the asset bundle $A_{it}$. Assets are weighted by their marginal contribution to livelihood. The main advantage of the $LWAI$ over the other resilience metrics is that the weights can be estimated flexibly, accounting for the interactions across returns to assets. Unlike factor and principal component analysis, the $LWAI$ provides a convenient livelihood metric expressed in poverty lines units. Household totalizing a one-unit LWAI own an asset portfolio that predicts a livelihood at the poverty line.

The construction of the livelihood-weighted asset index involves two steps. First, the weights are estimated by a regression of the livelihood of household $i$ ($l_{it}$) on the vector of assets $A_{it}$:

$$l_{it} = \sum_{j} \varphi_j(A_{it})A_{ijt} + \varepsilon_{it} \tag{21}$$

where $\varphi_j(A_{it})$ is the weight of asset $j$ and $\varepsilon_{it}$ the error term. The subscripts $i$, $j$ and $t$ are respectively used for household (i), asset (j) and time period (t). A quadratic term is included in (21) to account for non-linearity in return to assets. The livelihood measure $l_{it}$ is the ratio of the household expenditures to the poverty line. Household expenditures are computed from the survey data while the monthly adult equivalent poverty line is obtained from the 2006 and 2015 Kenya Household Surveys. The poverty line is a per capita minimum income that categorizes households as non-poor in Kenya. We scale the poverty line to account for the household size and composition using the Organization for Economic Co-operation and Development (OECD) scale S (Bittman and Goodin, 2000):

$$S = (1 + 0.7 \times ([Number\ of\ adults] - 1) + 0.5 \times [Number\ of\ children]) \tag{22}$$

Children include household members aged 15 and below.

The estimates of assets weights $\hat{\varphi}_j$ obtained in (21) are used to calculate the livelihood-weighted asset index:

$$LWAI(A_{it}) = \sum_j \hat{\varphi}_j(A_{it})A_{ijt} \tag{23}$$

The assets consist of 3 categories: natural capital (land), human capital and productive capital (equipment). To reduce the number of items included in the latter category, they are aggregated in five sub-categories: non-motorized mobility, vehicles, farm machinery and equipment, building and improvement (Table 3.1) and livestock inventory expressed as tropical livestock units (TLU) with: 1 TLU = 1 cow = 0.7 camel = 10 sheep or goats.

**Table 3.1 Sub-categories of productive capital**

| Sub-Category | Non-motorized mobility | Vehicles and motorized | Farm machinery and equipment | Building and improvement |
|---|---|---|---|---|
| Items | Bicycle<br>Wheelbarrow<br>Carts | Tuktuk<br>Car<br>Truck<br>Tractors<br>Motorcycle | Power saw<br>Chaff cutter<br>Sprayer<br>Sheller<br>Grinder | Grazing unit<br>Feeding units<br>Poultry<br>Irrigation equipment<br>Ploughs<br>Cattle dip<br>Stores |

Equation (21) is estimated by a year and district fixed effect panel and results are reported in Table 3.5.

## Econometric model

From the theoretical results, it follows that households using mobile money could receive support from a wider network when facing income shocks and exhibit more resilience than their non-users counterpart. To test this relationship, we construct a resilience score based on the econometric method proposed by Cissé and Barrett (2018) that we regress on the distance to the nearest mobile money agent and control variables using a four rounds panel. The model consists of three equations estimated consecutively. First, we regress the LWAI measure ($W_{it}$) obtained in (23) on a polynomial function of the lagged LWAI ($W_{i,t-1}$) and other covariates assuming a first order Markov process:

$$W_{it} = \sum_{k=1}^{n} \beta_{Mk} W_{i,t-1}^{k} + \alpha_M MM_{it} + \omega_M X_{it} + \varepsilon_{Mit} \tag{24}$$

As pointed out by Cissé and Barrett (2018), only one lag is necessary to summarize previous states of well-being. Another benefit to controlling for a single lag period is to avoid or mitigate multicollinearity from including two left-hand side variables which dependence is non-stochastic for obvious reasons. The polynomial lagged asset included in (24) accounts for the nonlinear expected well-being dynamics (Barrett and Constas, 2014). A polynomial of order 3 is preferred to mirror the S-Shaped dynamic nonlinear path. In fact, a cubic specification is the most parsimonious specification to accounts for the S-Shape. The variable of interest $MM_{it}$ consists of the distance to the nearest mobile money retailer expressed in kilometers. We control for household characteristics $X_{it}$ as in Jack and Suri (2014), notably the household head's gender, age, education and main source of income. Household size and rural or urban residency complete the set of control variables and $\varepsilon_{it}$ is an idiosyncratic error term.

Assuming that the mean random error term of (24) is zero, we can estimate the predicted mean LWAI as follows (Just and Pope, 1979):

$$\widehat{W}_{it} = \sum_{k=1}^{n} \hat{\beta}_{Mk} W_{i,t-1}^{k} + \hat{\alpha}_M MM_{it} + \widehat{\omega}_M X_{it} \qquad (25)$$

The conditional variance is obtained by squaring the residuals of (24) and expressed as the following conditional variance equation:

$$\sigma_{it}^2 = \sum_{k=1}^{n} \beta_{Vk} W_{i,t-1}^{k} + \alpha_V MM_{it} + \omega_V X_{it} + \varepsilon_{Vit} \qquad (26)$$

Note that the indices *M* and *V* on the coefficient in (24), (25) and (26) refer to the mean and variance equation coefficients. As in (25), we assume that the random error terms of (26) have a zero-mean and estimate the following conditional variance:

$$\hat{\sigma}_{it}^2 = \sum_{k=1}^{n} \hat{\beta}_{Vk} W_{i,t-1}^{k} + \hat{\alpha}_V MM_{it} + \widehat{\omega}_V X_{it} \qquad (27)$$

The estimates of the mean $\widehat{W}_{it}$ and the variance $\hat{\sigma}_{it}^2$ LWAI can be used to estimate each household probability density function (pdf) over each round of the survey, assuming the two predicted conditional moment are normally, log-normally or gamma-distributed. The kernel density plots of $\widehat{W}_{it}$ and $\hat{\sigma}_{it}^2$ are presented in Appendix B. Using the pdf of each household, we construct the development resilience score, that is the probability to exceed a threshold level $\overline{W}$ of assets holding (LWAI): $\Pr(W_{it} > \overline{W})$. The resilience score is regressed on the same set of covariates as in (17) and (19):

$$\rho_{it}^2 = \sum_{k=1}^{n} \beta_{Rk} W_{i,t-1}^k + \alpha_R MM_{it} + \omega_R X_{it} + \varepsilon_{Rit} \tag{28}$$

If mobile money is predicted to increase resilience to shocks, households residing near to a mobile money agent should exhibit a higher resilience to shocks than their counterparts living further from any mobile money retailer, ceteris paribus. Since the instrument for mobile money is the distance between household and mobile money retailer, the regression should yield a negative estimate of the mobile money coefficient in the mean (24) and the resilience (28) equations. As to the variance equation, the relationship between distance to a mobile money retailer and variance LWAI could take any direction. A positive coefficient would indicate that access to mobile money shrinks the variability of asset levels across years, which would imply that households hold a stable asset base across years as a result of mobile money access. The opposite direction could be interpreted as a loss or a gain in productive assets depending on the evolution of the LWAI over the 4 rounds of the survey. The previous year's level of asset holdings lag-LWAI should positively affect the current year of asset holding since we limit the period between the two wellbeing states to a year.

The first and second conditional moments are derived to estimate the probability of a household holding a level of asset above a defined threshold $\bar{W}$ which is the development resilience indicator. We assume a gamma distribution to estimate the probability density functions resulting from the conditional moments. Alternative distributions are considered and results are reported in Appendix B. The estimates are consistent across specifications based on a log-normal distribution.

- Shocks

To specifically capture the mutual insurance pathway, we include an interaction term that relates the distance to the nearest agent to a negative shock dummy taking the value of 1 for moderate to severe shocks and zero otherwise. Negative shocks are rated on a scale ranging from 1 to 5 from which only levels 3 to 5 are accounted for by the dummy. Moderate to severe shocks are preferred for their higher potential to require assistance and their higher likelihood to induce asset depletion as households respond more differently to lower magnitude shocks than higher magnitude shocks. Formally, we include the interaction term to (24), (26) and (28) as follows:

$$Q_{ijt} = \sum_{k=1}^{n} \beta_{jk} W_{i,t-1}^{k} + \alpha_j MM_{it} + \omega_j X_{it} + \delta_{ijt}.Shock.MM_{it} + \varepsilon_{jit} \quad (29)$$

where *Shock* denotes the shock dummy and the subscript *j* takes the values of 1, 2 and 3 respectively for the first moment, second moment and development resilience equations. A negative coefficient estimate $\delta_{ijt}$ would indicate a smaller marginal well-being loss to mobile money users relative to their non-user counterparts.

## Data and descriptive statistics

The analysis is based on data from a national survey carried out in Kenya over five rounds in August-October 2008 (Round 1), October 2009 to January 2010 (Round 2), May to

August 2010 (Round 3), March to June 2011 (Round 4) and June to September 2014 (Round 5). In year 1, 3000 randomly selected households were interviewed in all regions of Kenya, with only 8% of the population not included in the sampling for logistical reasons. As part of the survey, mobile money usage and agent data were collected. We exploit data from Round 1, 2, 3 and 5 since round 4 was not made publicly available. Table 3.2 summarizes selected statistics by survey round. Data form the province of Nairobi was not collected across the four rounds of the survey, leading to a relatively high attrition rate in rounds 2, 3 and 5. Our population of inference, therefore, excludes the metropolitan area of Nairobi. Additional, Jack and Suri find that the attrition rate does not affect the estimation of the effect of mobile money. The final sample consists of 1094 households from 6 provinces of Kenya: Central, Eastern, Rift Valley, Western, Nyanza, and Coast.

**Table 3.2 Selected statistics by survey rounds**

| | **Round 1** | **Round 2** | **Round 3** | **Round 5** |
|---|---|---|---|---|
| Year | 2008 | 2009 | 2010 | 2014 |
| Sample Households | 3,000 | 2,016 | 1,531 | 1,688 |
| Number of Accounts (million users) | 4 | 8 | 13 | 25.4 |
| Access to formal credit (# households) | | | 135 | 278 |
| Attrition Rate (% ) | | 33% | 49% | 44% |
| Number of Agents | 4,000 | 16,000 | 20,000 | 125,000 |

One of the assumptions of the theoretical model is poor access to credit markets. Only 9% of the surveyed households in round 3 have access to a formal credit institution such as banks, microfinance institutions or large corporations. This rate increases to 16% in round 5, yet it includes the loans that households obtain to finance business expenditures and durable goods. In round 5, only 16% of the households that have access to credit were lent an amount for emergency purposes, supporting the assumption that the surveyed households are for the most borrowing-constrained.

Table 3.3 shows the sample summary statistics disaggregated by mobile money usage status. The p-value of the mean difference between mobile money users and non-users is reported in row 5 of each panel. The mobile money user is on average more educated, urban dweller and likely to hold a non-farm occupation. These differences trends are consistent across the 4 rounds of the survey considered in the analysis. Mobile money users are also younger than their non-users counterparts as expected. In round 1 and 3, no significant gender difference is observed in the sample, though a higher proportion of male utilizes the mobile money technology. The mean household size of the sample is consistent with the average household size of 4 persons in 2014 reported by United Nations. The household size is comparable across users and non-users in rounds 2 and 3. In general, mobile money users differ from non-users counterparts but this gap varies across surveys except for education, rural/urban residence and main occupation.

**Table 3.3 Summary statistics (N = 1061)**

| | | Age | Male | Education | Rural | Farmer | Size | |
|---|---|---|---|---|---|---|---|---|
| **Round 1** | | | | | | | | |
| Non User | Mean | 46.749 | 0.776 | 6.890 | 0.537 | 0.363 | 4.791 | (1) |
| | SD | (16.367) | (0.417) | (4.650) | (0.499) | (0.481) | (2.268) | (2) |
| User | Mean | 42.643 | 0.764 | 8.565 | 0.285 | 0.164 | 4.300 | (3) |
| | SD | (13.920) | (0.425) | (5.349) | (0.452) | (0.371) | (2.133) | (4) |
| Difference | p-value | 0.000 | 0.662 | 0.000 | 0.000 | 0.000 | 0.000 | (5) |
| **Round 2** | | | | | | | | |
| Non User | Mean | 50.259 | 0.725 | 5.574 | 0.588 | 0.451 | 4.787 | (1) |
| | SD | (17.036) | (0.447) | (4.362) | (0.493) | (0.498) | (2.438) | (2) |
| User | Mean | 72.081 | 0.799 | 8.396 | 0.375 | 0.213 | 4.825 | (3) |
| | SD | (520.498) | (0.401) | (5.013) | (0.484) | (0.410) | (2.232) | (4) |
| Difference | p-value | 0.451 | 0.008 | 0.000 | 0.000 | 0.000 | 0.802 | (5) |
| **Round 3** | | | | | | | | |
| Non User | Mean | 50.848 | 0.769 | 6.072 | 0.631 | 0.435 | 4.524 | (1) |
| | SD | (16.942) | (0.422) | (4.369) | (0.483) | (0.496) | (2.517) | (2) |
| User | Mean | 45.252 | 0.816 | 8.237 | 0.348 | 0.215 | 4.538 | (3) |
| | SD | (13.594) | (0.388) | (5.125) | (0.477) | (0.411) | (2.174) | (4) |
| Difference | p-value | 0.000 | 0.073 | 0.000 | 0.000 | 0.000 | 0.929 | (5) |
| **Round 5** | | | | | | | | |
| Non User | Mean | 64.342 | 0.579 | 4.486 | 0.895 | 0.658 | 3.026 | (1) |
| | SD | (19.577) | (0.500) | (4.087) | (0.311) | (0.481) | (2.444) | (2) |
| User | Mean | 49.734 | 0.776 | 7.639 | 0.424 | 0.273 | 5.383 | (3) |
| | SD | (13.468) | (0.417) | (4.989) | (0.494) | (0.446) | (2.406) | (4) |
| Difference | p-value | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | (5) |

These differences coupled with reported self-selection issues lead us to utilize the distance separating each household to the nearest mobile money agent as a proxy for mobile money use. The justification for this approach is provided in the method section. Table 3.4 displays the distance summary statistics by survey rounds. The mean distance to the nearest mobile money retailer shrinks considerably from the first survey round in 2008 to the 5$^{th}$ round in 2014 confirming the fast-growing mobile money agent network in Kenya over this period. More importantly, Kenyan households have to travel 17% fewer kilometers to reach a mobile money retailer over the period covering the second round of the survey. This increase in coverage between round 1 and 2 is the highest, although the number of mobile money agents in the entire country has the most increased between round 3 and 5. The median distance follows a similar reduction trend across the survey rounds.

**Table 3.4 Distance summary statistics by survey round (N = 1061)**

| Variable | Round 1 | Round 2 | Round 3 | Round 5 |
|---|---|---|---|---|
| Mean (km) | 8.09 | 6.65 | 5.37 | 5.01 |
| Standard deviation | 11.81 | 10.31 | 9.76 | 9.44 |
| Min (km) | 0 | 0 | 0 | 0 |
| First quartile (km) | 0.8 | 0.5 | 0.5 | 0.38 |
| Median (km) | 3 | 2 | 2 | 1.5 |
| Third quartile (km) | 10 | 7 | 5 | 5 |
| Max (km) | 70 | 70 | 70 | 70 |

## Results and discussion

This section presents the results of the model estimations. Table 3.5 presents the estimates of the three model specification of the weight equation regression. In all models, the ratio of household expenditures to the adjusted poverty line is regressed on a set of explanatory variables. Model 2 includes a quadratic term of each variable to the set of explanatory variables to account for decreasing marginal returns. In model 3, we allow a year and province fixed effects to control for year and location-specific unobserved factors. All equations are estimated as a panel by maximum likelihood.

Tractor and car ownership contribute heavily to livelihood, almost twice the weight of farm and non-farm micro-enterprise equipment, both assets making the highest overall contribution to livelihood. Households who own this specialized set of equipment are likely to spend more relative to their less specialized counterparts. In contrast, it is not surprising that non-motorized vehicles such as bicycles and carts yield a lower contribution to livelihood. Such equipment is own by more than 90% of the surveyed households and makes little difference. The education level of the household head and land ownership contribute to livelihood to a lesser extent than vehicle and equipment. A striking fact is the negative weight associated with the number of adults in the household. This is not surprising when we consider that: (i) it is common to observe multiple adults living under the same roof in Sub-Saharan Africa, and (ii) those adults are generally unemployed or hold a low paying job, making the marginal contribution of a second or third adult to livelihood relatively insignificant. Land improvement and Tropical Livestock Units are not statistically significant in the model. The difference in the province estimates could reflect the economic disparities between regions of Kenya.

**Table 3.5 Estimates of the weights equation**

| Household livelihood | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Non motor | 1.61 (0.52) | *** | 1.36 (0.80) | * | 1.28 (0.81) | |
| Non-motor$^2$ | | | 0.02 (0.08) | | 0.03 (0.08) | |
| Vehicle | 7.96 (1.10) | *** | 12.21 (1.89) | *** | 11.88 (1.90) | *** |
| Vehicle$^2$ | | | -1.34 (0.45) | *** | -1.25 (0.45) | *** |
| Equipment | 7.12 (1.50) | *** | 9.63 (2.82) | *** | 6.39 (2.88) | ** |
| Equipment$^2$ | | | -1.40 (1.08) | | -0.71 (1.09) | |
| Land improvement | 0.07 (0.16) | | 0.52 (0.35) | | 0.30 (0.36) | |
| Land improvement$^2$ | | | 0.00 (0.00) | | 0.00 (0.00) | |
| Adults | -3.01 (0.38) | *** | -8.30 (1.30) | *** | -8.33 (1.29) | *** |
| Adults$^2$ | | | 0.66 (0.16) | *** | 0.67 (0.16) | *** |
| Years of education | 0.30 (0.12) | ** | 0.28 (0.12) | ** | 0.27 (0.12) | ** |
| TLU | 0.10 (0.17) | | 0.17 (0.26) | | 0.33 (0.26) | |
| TLU$^2$ | | | 0.00 (0.00) | | 0.00 (0.00) | |
| Land | 0.07 (0.04) | | 0.18 (0.10) | * | 0.19 (0.10) | ** |
| Land$^2$ | | | 0.00 (0.00) | | 0.00 (0.00) | * |
| Eastern | | | | | -5.68 (2.06) | *** |
| Rift Valley | | | | | -3.67 (1.85) | ** |
| Western | | | | | -9.49 (2.05) | *** |
| Nyanza | | | | | -6.67 (1.89) | *** |
| Coast | | | | | -2.45 (2.04) | |
| Intercept | 22.13 (1.53) | | 29.61 (2.41) | | 34.43 (2.69) | |
| Polynomial term | No | | **Yes** | | **Yes** | |
| Year fixed effect | No | | No | | **Yes** | |
| Province Fixed effect | No | | No | | **Yes** | |
| Observations | 4325 | | 4325 | | 4325 | |

*, ** and *** denote significance at the 1%, 5% and 10% levels.

One concern that could be raised is the absence of variables that capture hours worked and savings, factors that also contribute to production. While hours worked can be approximated by the number of adults in the household, savings data were not available. Yet, it is worthwhile mentioning that (21) is estimated for the main purpose of deriving a set of weights, and less for the interest of determining the exact contribution to livelihood. The estimates in Table 3.5 are used to compute the LWAI for each household.

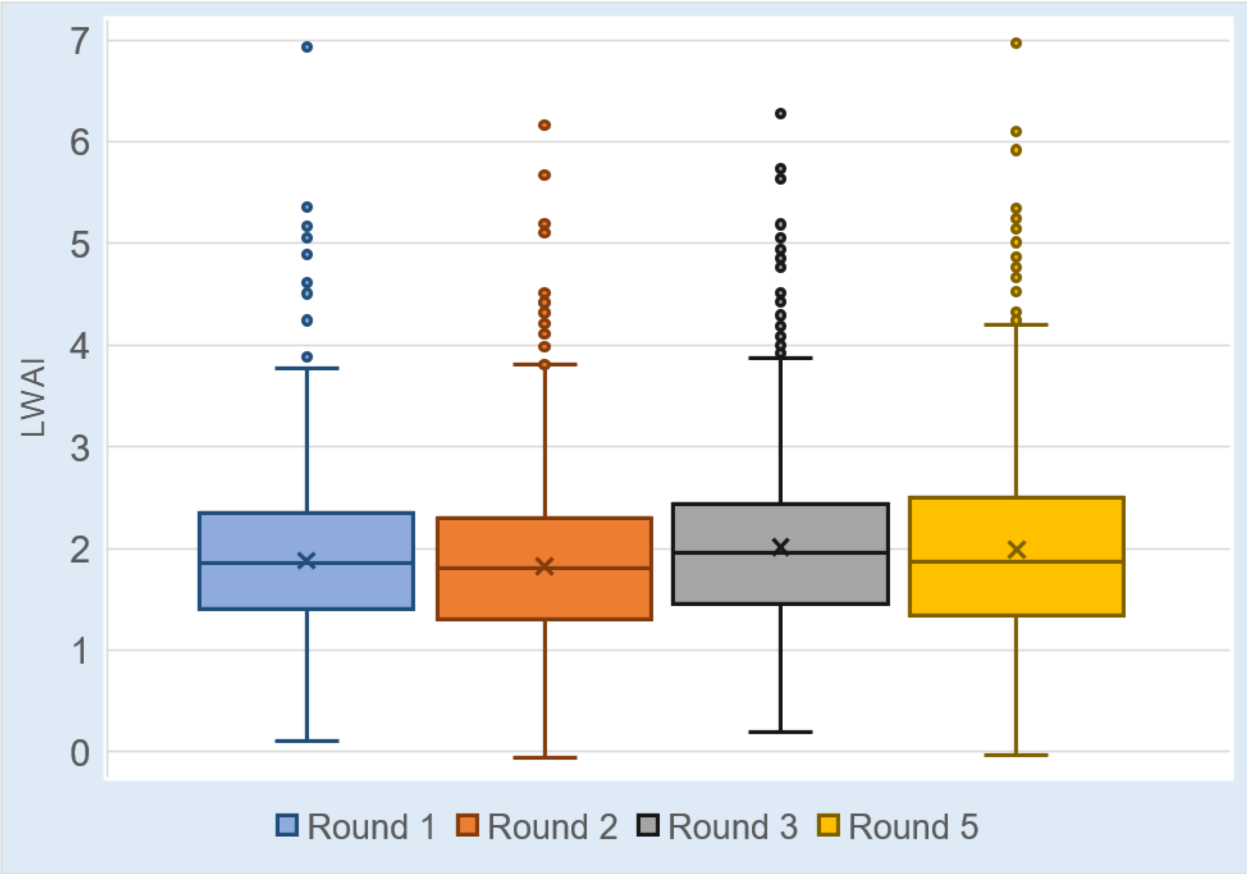


**Figure 3.3 LWAI univariate statistics by survey round**

Figure 1 shows the LWAI univariate statistics by survey rounds. The sample presents comparable interquartile ranges across survey rounds, with a median lower than 2. Less than 25% of the households have a LWAI lower than the asset poverty line (LWAI = 1). Although households adopt different production technologies that may lead to different productivity level for the same asset bundle, we assume that households face the same production technology for comparison purposes. That is, the LWAI should not be considered as the poverty level, but as the asset bundle that predicts each household poverty level. The median LWAI is larger in round 3 and 5, and the lowest in round 2.

The LWAI is regressed on a polynomial function of lagged LWAI, mobile money and a set of household characteristics to investigate the effect of mobile money of development resilience. Table 3.6 shows the estimate of the mean, variance and development resilience equations. The models are estimated by maximum likelihood as a Poisson regression (mean and variance models) and a negative binomial regression (development resilience model). The estimates cannot be used to make inferences but offer an insight of the statistically significant variables and the direction of the relationship between the outcome of interest and the set of covariates. The Development resilience equation estimation has the best fit based on the Bayesian Information Criterion (BIC) and shows statistical significance for all covariates. The estimates of the polynomial lag assets support the existence of a nonlinear relationship between the asset-based outcomes (mean asset and development resilience) and the previous year's asset level, showing a 1% significance level. Specifically, the negative sign of the quadratic term suggests a non-linear asset dynamics path, as in Cissé and Barrett (2018).

The mobile money access estimate is negative as expected but only statistically significant in the development resilience model. The negative sign suggests that households closer to a mobile money retailer have a higher likelihood of exceeding the asset poverty line. The lack of statistical significance of the mobile money estimate in the mean equation may seem surprising. Yet, the mean equation only presents the short-run relationship between mobile money and well-being while the development resilience looks at the longer-term ability to withstand shocks. Previous mobile money literature found that mobile money contributed to smooth consumption in the presence of shocks (Jack and Suri, 2014) but provide no evidence of mobile money impact on wealth. A possible explanation to seemingly contradictory results could lay in the nature of the outcome. When looking at static measures of well-being, improved risk-sharing is less likely to affect durable goods such as productive assets. However, in the presence of long term stressors, when durables goods are at risk of depletion, improved risk-sharing through mobile money could mitigate asset depletion.

**Table 3.6 Estimates of the mean, variance and resilience equation**

| | Mean equation | | Variance equation | | Development resilience | |
|---|---|---|---|---|---|---|
| lag(LWAI) | 0.610 (0.08) | *** | 0.510 (0.41) | | 0.421 (0.03) | *** |
| lag(LWAI)^2 | -0.162 (0.03) | *** | -0.006 (0.15) | | -0.031 (0.01) | *** |
| lag(LWAI)^3 | 0.016 (0.00) | *** | -0.005 (0.02) | | 0.000 (0.00) | |
| Mobile money | -0.004 (0.00) | | -0.069 (0.04) | | -0.052 (0.00) | *** |
| Male headed | -0.001 (0.02) | | -0.034 (0.13) | | -0.020 (0.00) | *** |
| Age | 0.001 (0.00) | | 0.084 (0.02) | *** | 0.064 (0.00) | *** |
| Age^2 | 0.000 (0.00) | | -0.001 (0.00) | *** | 0.000 (0.00) | *** |
| Years of education | 0.016 (0.00) | *** | 0.026 (0.01) | ** | 0.016 (0.00) | *** |
| Household size | -0.056 (0.00) | *** | 0.064 (0.03) | ** | 0.038 (0.00) | *** |
| Rural | 0.055 (0.02) | *** | -0.065 (0.11) | | -0.037 (0.00) | *** |
| Farmer | 0.000 (0.02) | | -0.078 (0.13) | | -0.052 (0.00) | *** |
| Shock | 0.028 (0.03) | | -0.008 (0.20) | | -0.006 (0.01) | |
| Shock * Mobile money | -0.037 (0.03) | | -0.272 (0.19) | | -0.178 (0.01) | *** |
| Round 2 | -0.045 (0.02) | *** | 0.137 (0.14) | | 0.097 (0.00) | *** |
| Round 3 | 0.036 (0.02) | ** | 0.203 (0.14) | | 0.134 (0.00) | *** |
| Round 5 | 0.089 (0.02) | *** | 0.500 (0.15) | *** | 0.340 (0.00) | *** |
| Eastern | -0.175 (0.02) | *** | 0.411 (0.16) | *** | 0.342 (0.00) | *** |
| Rift valley | -0.070 (0.02) | *** | 0.274 (0.17) | | 0.243 (0.00) | *** |
| Western | -0.307 (0.03) | *** | 0.321 (0.19) | * | 0.267 (0.01) | *** |
| Nyanza | -0.156 (0.02) | *** | 0.391 (0.14) | *** | 0.335 (0.00) | *** |
| Coast | -0.047 (0.02) | ** | 0.277 (0.16) | * | 0.238 (0.00) | *** |
| Intercept | 0.192 (0.10) | ** | -5.255 (0.64) | *** | -3.956 (0.03) | *** |
| N | 3107 | | 3107 | | 3130 | |
| BIC | -24144.091 | | -21957.067 | | -25013.466 | |

*, ** and *** denote significance at the 1%, 5% and 10% levels.

The interaction term between shocks and mobile money is added to the model specification to investigate the impact of mobile money on asset holdings when facing a severe shock. Consequently, we consider shocks rated as severe (3 to 5 on a scale of 5) by the surveyed households. As shown in Figure 2, most households would avoid selling their assets to cope with a shock until they face a severe shock, relying on savings and other coping mechanisms on less severe shocks. Because severe shocks have usually a lasting effect on households, they will more likely affect resilience. The estimate of the interaction term is statistically significant in the resilience equation, confirming that mobile money reduces the probability of asset depletion in the presence of severe shocks.

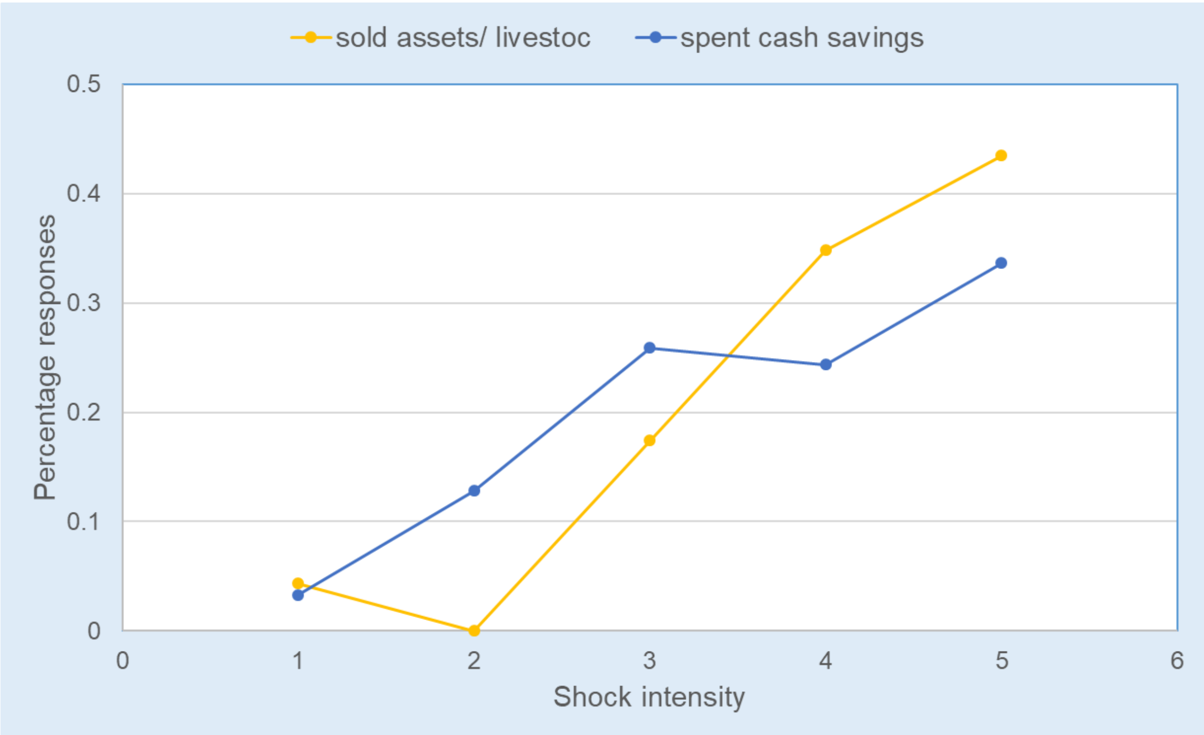


**Figure 3.4 Households responses to shocks by levels of shock severity**

The negative estimate of the interaction term is in Table 3.6 can be interpreted as the additional shock effect induced by the access to a mobile money agent. Because this additional effect increases with distance in absolute value, households living closer to a mobile money agent are less vulnerable to severe shocks than lower mobile money access households, consistent with Jack and Suri (2014).

**Table 3.7 Marginal effects of the mean, variance and development resilience equations**

**Panel A: Marginal effects of the mean equation**

| | Poverty line | | Median | | Third quartile | |
|---|---|---|---|---|---|---|
| Lag(LWAI) | 0.521 (0.05) | *** | 0.327 (0.03) | *** | 0.218 (0.03) | *** |
| Mobile money | -0.009 (0.01) | | -0.011 (0.01) | | -0.012 (0.01) | |
| Shock*Mobile.M | -0.058 (0.04) | | -0.072 (0.06) | | -0.077 (0.06) | |
| Gender | -0.002 (0.03) | | -0.003 (0.03) | | -0.003 (0.03) | |
| Age | -0.002 (0.00) | * | -0.002 (0.00) | * | -0.002 (0.00) | * |
| Education | 0.025 (0.00) | *** | 0.030 (0.00) | *** | 0.033 (0.00) | *** |
| Household size | -0.087 (0.01) | *** | -0.108 (0.01) | *** | -0.116 (0.01) | *** |
| Rural | 0.086 (0.03) | *** | 0.106 (0.03) | *** | 0.114 (0.03) | *** |
| Farmer | 0.000 (0.03) | | 0.000 (0.03) | | 0.000 (0.04) | |
| N | 3099 | | 3099 | | 3099 | |

**Panel B: Marginal effects of the variance equation**

| | Poverty line | | Median | | Third quartile | |
|---|---|---|---|---|---|---|
| Lag(LWAI) | 0.135 (0.04) | *** | 0.180 (0.04) | *** | 0.203 (0.05) | *** |
| Mobile money | -0.023 (0.01) | ** | -0.035 (0.02) | ** | -0.043 (0.02) | ** |
| Shock*Mobile.M | -0.076 (0.05) | | -0.113 (0.08) | | -0.140(0.09) | |
| Gender | -0.009 (0.03) | | -0.014 (0.05) | | -0.017 (0.07) | |
| Age | 0.006 (0.00) | *** | 0.009 (0.00) | *** | 0.011 (0.00) | *** |
| Education | 0.007 (0.00) | ** | 0.011 (0.00) | ** | 0.013 (0.01) | ** |
| Household size | 0.018 (0.01) | ** | 0.026 (0.01) | ** | 0.033 (0.01) | ** |
| Rural | -0.018 (0.03) | | -0.027 (0.05) | | -0.033 (0.06) | |
| Farmer | -0.022 (0.04) | | -0.032 (0.05) | | -0.040 (0.06) | |
| N | 3099 | | 3099 | | 3099 | |

**Panel C: Marginal effects of the development resilience equation**

| | Poverty line | | Median | | Third quartile | |
|---|---|---|---|---|---|---|
| Lag(LWAI) | 0.066 (0.00) | *** | 0.063 (0.00) | *** | 0.058 (0.00) | *** |
| Mobile money | -0.012 (0.00) | *** | -0.013 (0.00) | *** | -0.014 (0.00) | *** |
| Shock*Mobile.M | -0.033 (0.00) | *** | -0.037 (0.00) | *** | -0.039 (0.00) | *** |
| Gender | -0.004 (0.00) | *** | -0.004 (0.00) | *** | -0.004 (0.00) | *** |
| Age | 0.003 (0.00) | *** | 0.004 (0.00) | *** | 0.004 (0.00) | *** |
| Education | 0.003 (0.00) | *** | 0.003 (0.00) | *** | 0.004 (0.00) | *** |
| Household size | 0.007 (0.00) | *** | 0.008 (0.00) | *** | 0.008 (0.00) | *** |
| Rural | -0.007 (0.00) | *** | -0.008 (0.00) | *** | -0.008 (0.00) | *** |
| Farmer | -0.010 (0.00) | *** | -0.011 (0.00) | *** | -0.011 (0.00) | *** |
| N | 3099 | | 3099 | | 3099 | |

*, ** and *** denote significance at the 1%, 5% and 10% levels.

## Marginal effects

The marginal effects of each equation are estimated at the poverty line, the median and the third quartile and reported in table 3.7. Panel A reports the marginal effects of the mean equation while panels B and C present the marginal effects of the variance and development resilience equations. The coefficient estimate on lag asset is statistically significant and decreasing in magnitude with quartiles in both mean and resilience equations. For households at the poverty line, the return to an additional index unit of productive assets is more than twice as of the third quartile. In contrast the education estimate at the third quartile exceeds is higher than at the poverty line. This could suggest that poorer households maximize returns to tangible while wealthier households maximize returns on human capital. As one would expect, previous asset holdings play a more prominent role in the probability of the poorer households to exceed the poverty line by 6 percentage points relative to the households at the third quartile of the LWAI. Mobile money was found to affect the current level of assets only when households face severe shocks as shown in Panel A of Table 3.7. This result somewhat contradicts the finding of Suri and Jack (2016) where the monetary value of household assets was used as a proxy for well-being, though their study does not primarily focus on the relationship between wealth and negative shocks. As predicted by the theoretical model, households facing a negative income shock could draw on a wider network of individuals to receive assistance. This would especially prevent households who adopt a consumption smoothing strategy to deplete their productive assets to maintain their level of consumption. The mobile money estimates of the variance equation show a positive relationship between mobile money access and LWAI variance. While this result may look surprising, these could be drawn by users that experienced large changes in their asset holdings during this period. For example, a large increase in asset holdings could be captured by these estimates.

The estimates in Panel C (Table 3.7) suggest that a 10 km reduction in the distance separating households to the nearest mobile money agent increases the probability of exceeding the poverty line by 1 percentage points. This result has important implications for households in the vicinity of the poverty line, as mobile money could prevent them from falling to a lower equilibrium. Additionally, mobile money users facing severe shocks are by 3 percentage points less likely to fall under the poverty line. This effect increases to 4 km for households in the 3rd quartile.

**LWAI Dynamics**

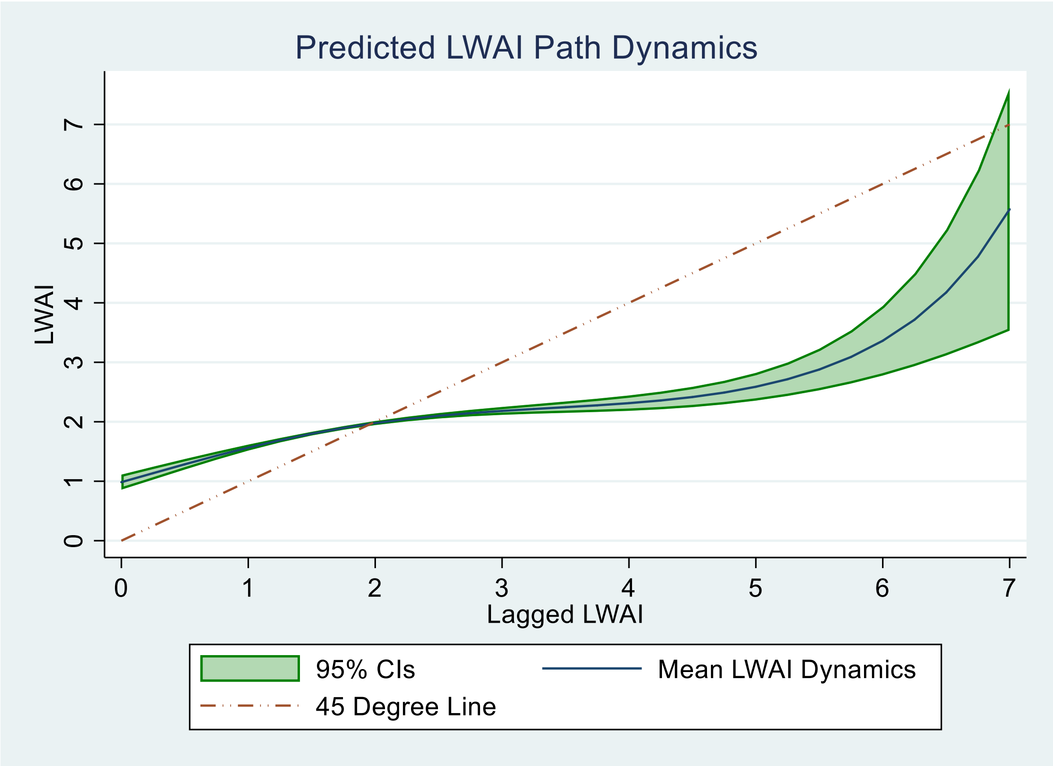


**Figure 3.5 Predicted LWAI dynamics**

The LWAI path dynamics are presented in Figure 2 from which two conclusions could be drawn. First, LWAI dynamics are non-linear, consistent with previous research on poverty traps. However, we find no evidence of multiple equilibrium poverty traps as suggested by previous research. A single steady-state equilibrium poverty traps is established at about 2 LWAI, as suggested in recent research on TLU dynamics (Cissé and Barrett, 2018; Phadera et al., 2019). The estimated steady-state equilibrium is higher than the static poverty line used to generate the livelihood asset weights. While this may seem surprising, a plausible interpretation of this higher poverty line level could be an underestimation of the minimum income that categorizes households as poor.

## Conclusion

Despite empirical evidence of the positive impact of mobile money on welfare, much of the empirical literature has not tested the long-run impact of mobile money on the ability to withstand shocks. Static measures of welfare based on consumption seem limited to determine the effect of mobile money on resilience, especially for households that adopt a consumption smoothing strategy. In this study, we estimate the impact of the distance to the nearest mobile money approach on household resilience using the development resilience indicator proposed by Barrett and Constas (2014). We found that a 10 km reduction in the distance separating households from the nearest mobile money retailer results in a percentage point increase in development resilience. Moreover, wealthier households are more likely to benefit from higher access to mobile money. When facing severe shocks, mobile money users were found capable of sustaining a higher probability of exceeding the asset poverty line than their non-user counterparts. These findings establish new evidence on the long-run effect of digital payments. The external validity of the findings is limited by the particularity of Kenya as the leading Sub-Saharan African country in adoption of digital payments. The high penetration of the technology and the longer period of exposure of households from all regions suggests that Kenyan households are more likely to use digital payments for various purposes. This is not necessarily true in countries where households are not yet acquainted with the technology. Interestingly, our forward-looking approach could allow us to predict the impact of mobile money on resilience at increasing levels of adoption in other countries.

The policy implications of these findings revolve around the facilitation of the expansion of digital technologies Because digital payments are found to have a long-run effect on resilience, their potential should not be hindered policies focusing on shorter terms outcomes.

Observing the rapid expansion of this technology, various countries envision fiscal policies aiming at increasing sales tax in this sector. While such policies may generate substantial revenues in the short run, the potential effects on vulnerable populations benefiting from this technology should be carefully considered. Depending on the behavioral response to taxation, it could undermine the potential of digital payment to strengthen resilience in areas where vulnerable populations are still struggling to meet their basing needs. As a risk management enhancing tool, mobile money could also complement the new or existing financial services being offered in rural areas.

One caveat to the methods hinges on the period covered by the datasets. As pointed by the poverty trap literature, sufficient time periods should be considered to effectively observe household welfare dynamics. Our dataset covering four rounds of survey including one-time period of lag limit the number of time periods to three, which may not allow us to accurately observe welfare dynamics and make accurate inferences. Another area of concern is the ability of the asset index to accurately capture welfare dynamic, particularly in the absence of data on savings and cash on hand. Finally, although our model predicts the average effect of mobile money on resilience at various levels of wealth, we still see the impact of the technology on asset smoothing households as a puzzle. Further studies could fruitfully explore these areas.

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# Chapter 4 - Conclusion

The two essays of this dissertation address two key issues: the impact of mobile money on smallholder market participation and resilience to shocks and stressors. The first essay develops and tests a conceptual model based on a transaction costs economics framework to explain how digital payments improve market participation. The estimation of a special regressor model shows that access to mobile money is associated with a reduction of the information asymmetry around the buyer type and an enhanced gain from distant market participation. The predictions of the conceptual model are empirically tested using an instrumental variable approach and secondary data from a cross-sectional survey conducted by the Consultative Group to Assist the Poor (CGAP) in Cote d'Ivoire and Tanzania. We specifically find that the probability of distant market participation is increased on average by 55 percentage points for mobile money users. Digital payments offer an innovative solution for addressing market failures due to high transaction costs, offering a new perspective to policymakers to improve efficiency in value chains and facilitate market linkages.

The second essay investigates the risk-sharing effect of mobile money on household development resilience. We first construct a multidimensional index of well-being based on productive assets holdings and empirically investigate the effect of mobile money on household development resilience using a conditional moment approach. The key findings suggest that a 10 km reduction in the distance separating households from the nearest mobile money retailer results in a percentage point increase in development resilience. Moreover, wealthier households are more likely to benefit from higher access to mobile money. The second essays contribute to the literature by establishing new evidence of the long-run effect of mobile money. In addition, by focusing on productive assets, this study provides evidence of a relationship between mobile money and risk management of income-generating activities. There are two major implications of this study. First, because digital payments are found to have a long-run effect on resilience, their potential should not be hindered policies focusing on shorter terms outcomes. Second, mobile money could complement the new or existing financial services being offered in rural areas for more sustainable effects.

# Appendix A -

**Table A.1 Mobile money model estimation (bivariate probit)**

| Dependent variable: Mobile money | | |
|---|---|---|
| Land size | 0.459 | ** |
| | (0.216) | |
| Access to agent | 0.132 | |
| | (0.113) | |
| Remittance | 0.054 | *** |
| | (0.011) | |
| Rainfall deviation | -0.144 | |
| | (0.200) | |
| Household size | 0.001 | |
| | (0.017) | |
| Male | 0.084 | |
| | (0.095) | |
| Age | 0.022 | |
| | (0.019) | |
| Age squared | 0.000 | |
| | (0.000) | |
| Land size | 0.001 | |
| | (0.001) | |
| Rural | -0.221 | ** |
| | (0.097) | |
| Tanzania | 0.217 | ** |
| | (0.106) | |

*, **, ** denote significance at the 1%, 5% and 10% levels.

**Table A.2 Marginal effects of the Special regressor model with additional variables**

| Dependent variable: Market participation | | |
|---|---|---|
| Rainfall deviation | 0.445 | *** |
| | (0.140) | |
| Mobile money | 0.575 | ** |
| | (0.287) | |
| Household size | -0.001 | |
| | (0.003) | |
| Household size | -0.012 | |
| | (0.024) | |
| Male | 0.000 | |
| | (0.005) | |
| Age | 0.000 | |
| | (0.000) | |
| Age squared | 0.018 | |
| | (0.023) | |
| Land size | -0.016 | |
| | (0.039) | |
| Rural | 0.010 | |
| | (0.022) | |
| Experience | 0.002 | |
| | (0.002) | |
| Land size | 0.000 | |
| | (0.000) | |
| Price information | -0.001 | |
| | (0.001) | |
| Rice | 0.034 | |
| | (0.035) | |
| Tanzania | -0.082 | ** |
| | (0.038) | |
| Livestock | -0.002 | |
| | (0.022) | |
| Intercept | -0.047 | |
| | (0.122) | |

*, **, ** denote significance at the 1%, 5% and 10% levels.

**Table A.3 Marginal effects of the Special regressor model with additional variables**

| Dependent variable: Market participation | | |
|---|---|---|
| Rainfall deviation | 0.054 | |
| | (0.047) | |
| Mobile money | 0.459 | *** |
| | (0.148) | |
| Household size | 0.011 | ** |
| | (0.005) | |
| Household size | 0.040 | |
| | (0.027) | |
| Male | 0.002 | |
| | (0.005) | |
| Age | 0.000 | |
| | (0.000) | |
| Age squared | 0.007 | |
| | (0.027) | |
| Land size | -0.064 | |
| | (0.047) | |
| Rural | -0.102 | *** |
| | (0.028) | |
| Experience | -0.003 | |
| | (0.003) | |
| Land size | 0.000 | |
| | (0.000) | |
| Price information | 0.001 | |
| | (0.001) | |
| Rice | 0.081 | ** |
| | (0.032) | |
| Tanzania | 0.014 | |
| | (0.036) | |
| Livestock | -0.011 | |

*, **, ** denote significance at the 1%, 5% and 10% levels.

# Appendix B -

**Figure B.1 Kernel density of the LWAI**

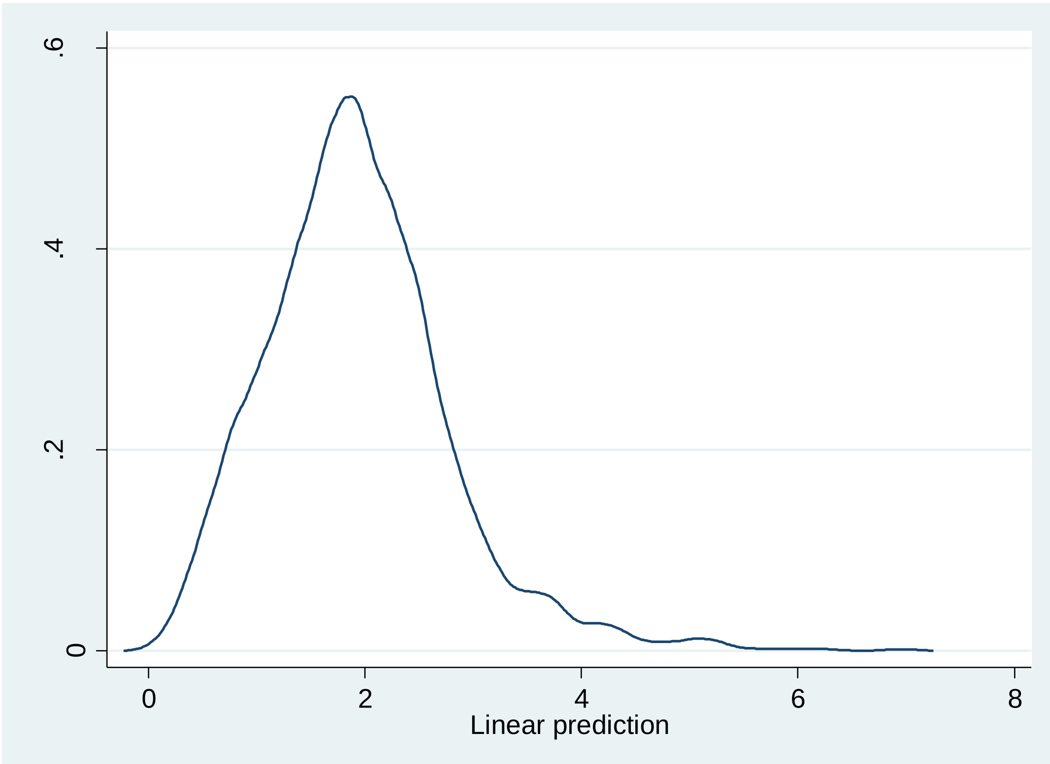

**Figure B.2 Kernel density of the Predicted probabilities**

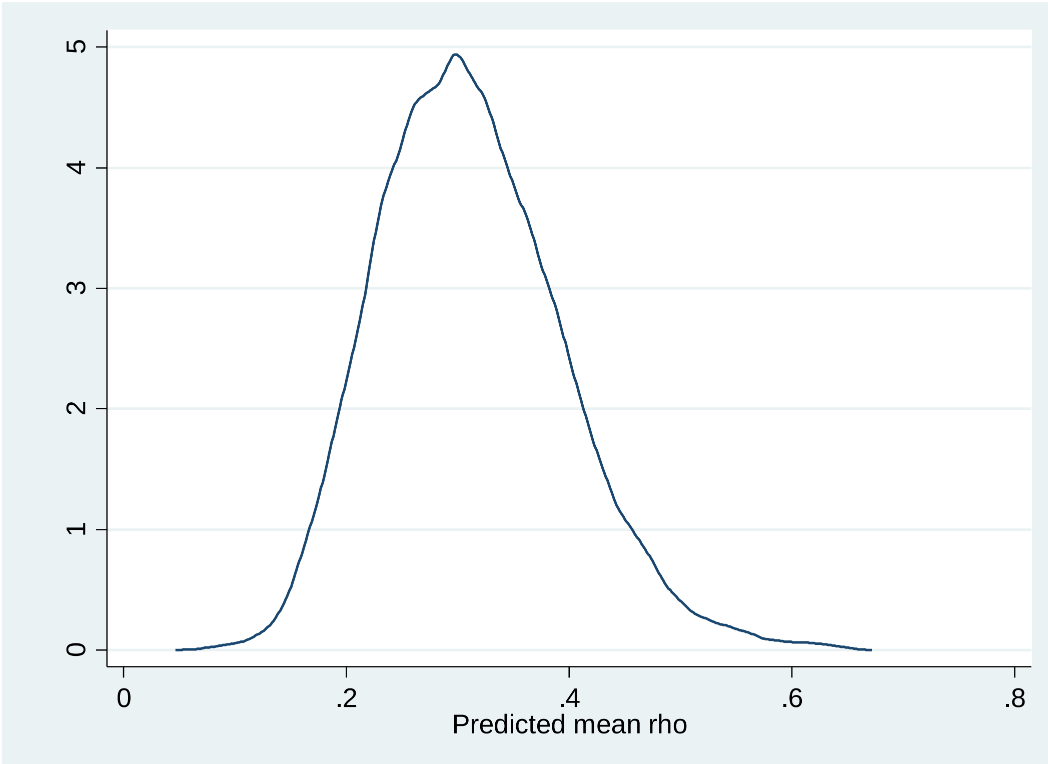

**Table B.4 Estimation based on Tropical Livestock Units (TLU)**

| | Mean equation | | Variance Equation | | Development resilience | |
|---|---|---|---|---|---|---|
| lag(LWAI) | 0.505 | *** | 0.166 | | 0.330 | *** |
| | (0.08) | | (0.41) | | (0.03) | |
| lag(LWAI)^2 | -0.127 | *** | -0.007 | | -0.093 | *** |
| | (0.03) | | (0.15) | | (0.01) | |
| lag(LWAI)^3 | 0.012 | *** | 0.005 | | 0.015 | *** |
| | (0.00) | | (0.02) | | (0.00) | |
| Mobile money | -0.005 | | -0.063 | | -0.048 | *** |
| | (0.01) | | (0.04) | | (0.00) | |
| Male headed | 0.002 | | 0.058 | | 0.040 | *** |
| | (0.02) | | (0.12) | | (0.00) | |
| Age | -0.001 | ** | 0.018 | *** | 0.013 | *** |
| | (0.00) | | (0.00) | | (0.00) | |
| Age^2 | 0.000 | ** | 0.000 | *** | 0.000 | *** |
| | (0.00) | | (0.00) | | (0.00) | |
| Years of education | 0.016 | *** | 0.037 | *** | 0.025 | *** |
| | (0.00) | | (0.01) | | (0.00) | |
| Household size | -0.053 | *** | 0.063 | ** | 0.038 | *** |
| | (0.00) | | (0.03) | | (0.00) | |
| Rural | 0.052 | *** | -0.144 | | -0.089 | *** |
| | (0.02) | | (0.11) | | (0.00) | |
| Farmer | -0.011 | | -0.130 | | -0.085 | *** |
| | (0.02) | | (0.12) | | (0.00) | |
| Shock | -0.015 | | -0.186 | | -0.124 | *** |
| | (0.03) | | (0.18) | | (0.01) | |
| Shock * Mobile money | -0.037 | * | -0.372 | | -0.247 | *** |
| | (0.02) | | (0.24) | | (0.01) | |
| Round 2 | -0.020 | | 0.163 | | 0.114 | *** |
| | (0.01) | | (0.15) | | (0.00) | |
| Round 3 | 0.060 | *** | 0.331 | ** | 0.221 | *** |
| | (0.02) | | (0.16) | | (0.00) | |
| Round 4 | 0.116 | *** | 0.685 | *** | 0.470 | *** |
| | (0.02) | | (0.14) | | (0.00) | |
| Eastern | -0.172 | *** | 0.352 | ** | 0.300 | *** |
| | (0.03) | | (0.17) | | (0.01) | |
| Rift valley | -0.077 | *** | 0.225 | | 0.211 | *** |
| | (0.02) | | (0.16) | | (0.00) | |
| Western | -0.335 | *** | 0.114 | | 0.128 | *** |
| | (0.03) | | (0.18) | | (0.01) | |
| Nyanza | -0.155 | *** | 0.360 | ** | 0.313 | *** |
| | (0.02) | | (0.16) | | (0.00) | |
| Coast | -0.060 | *** | 0.181 | | 0.175 | *** |
| | (0.02) | | (0.18) | | (0.01) | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 0.313 | | -3.140 | | -2.458 | |
| Intercept | (0.08) | *** | (0.45) | *** | (0.02) | *** |
| N | 3095 | | 3095 | | 3119 | |
| | - | | - | | - | |
| BIC | 24015.468 | | 21694.629 | | 24913.454 | |

**Table B.5 Estimation using 4 lags**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| lag(LWAI) | 0.735 | *** | 0.586 | | 0.682 | *** |
| | (0.14) | | (0.63) | | (0.06) | |
| lag(LWAI)^2 | -0.242 | *** | -0.059 | | -0.208 | *** |
| | (0.08) | | (0.40) | | (0.03) | |
| lag(LWAI)^3 | 0.035 | * | 0.009 | | 0.045 | *** |
| | (0.02) | | (0.10) | | (0.01) | |
| lag(LWAI)^4 | -0.002 | | -0.001 | | -0.004 | *** |
| | (0.00) | | (0.01) | | (0.00) | |
| Mobile money | -0.004 | | -0.067 | | -0.051 | *** |
| | (0.00) | | (0.04) | | (0.00) | |
| Male headed | -0.002 | | -0.034 | | -0.021 | *** |
| | (0.02) | | (0.13) | | (0.00) | |
| Age | 0.001 | | 0.084 | *** | 0.064 | *** |
| | (0.00) | | (0.02) | | (0.00) | |
| Age^2 | 0.000 | | -0.001 | *** | 0.000 | *** |
| | (0.00) | | (0.00) | | (0.00) | |
| Years of education | 0.016 | *** | 0.025 | ** | 0.016 | *** |
| | (0.00) | | (0.01) | | (0.00) | |
| Household size | -0.056 | *** | 0.063 | ** | 0.038 | *** |
| | (0.00) | | (0.03) | | (0.00) | |
| Rural | 0.055 | *** | -0.065 | | -0.037 | *** |
| | (0.02) | | (0.11) | | (0.00) | |
| Farmer | 0.000 | | -0.077 | | -0.051 | *** |
| | (0.02) | | (0.13) | | (0.00) | |
| Shock * Mobile money | -0.037 | | -0.273 | | -0.179 | *** |
| | (0.03) | | (0.19) | | (0.01) | |
| Round 2 | -0.045 | *** | 0.136 | | 0.097 | *** |
| | (0.02) | | (0.14) | | (0.00) | |
| Round 3 | 0.037 | ** | 0.201 | | 0.133 | *** |
| | (0.02) | | (0.14) | | (0.00) | |
| Round 4 | 0.090 | *** | 0.498 | *** | 0.340 | *** |
| | (0.02) | | (0.15) | | (0.00) | |
| Eastern | -0.177 | *** | 0.413 | *** | 0.341 | *** |
| | (0.02) | | (0.16) | | (0.00) | |
| Rift valley | -0.072 | *** | 0.277 | | 0.243 | *** |
| | (0.02) | | (0.17) | | (0.00) | |
| Western | -0.308 | *** | 0.326 | * | 0.269 | *** |
| | (0.03) | | (0.19) | | (0.01) | |
| Nyanza | -0.159 | *** | 0.395 | *** | 0.334 | *** |
| | (0.02) | | (0.14) | | (0.00) | |
| Coast | -0.049 | ** | 0.277 | * | 0.236 | *** |
| | (0.02) | | (0.16) | | (0.00) | |
| Intercept | 0.135 | | -5.279 | *** | -4.058 | *** |
| | (0.11) | | (0.61) | | (0.04) | |

| | | | |
|---|---|---|---|
| N | 3107 | 3107 | 3130 |
| BIC | - 24136.338 | - 21944.393 | - 25005.473 |